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The effects of income inequality on economic growth: evidence from China

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THE EFFECTS OF INCOME INEQUALITY ON ECONOMIC GROWTH: EVIDENCE FROM CHINA

Wencong Chen

A thesis submitted for the degree of Doctoral of Philosophy

University of Bath

Department of Economics

May 2018

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Signed on behalf of the Faculty of Humanity and Social Science.....

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List of Abbreviations

2SLS	2-Stage Least Square
ARDL	Autoregressive Distributive Lag
CHIP	Chinese Household Income Project
CIPS	Cross Sectionally augmented Im–Pesaran–Shin panel unit root test
CS-ARDL	Cross Sectionally augmented Autoregressive Distributive Lag
CSD	Cross Sectional Dependence
CS-DL	Cross Sectionally augmented Distributive Lag
DD	Difference-in-Differences
FE	Fixed Effects
GDP	Gross Domestic Product
GMM	General Method of Moments
IMF	International Monetary Fund
IPS	Im–Pesaran–Shin panel unit root test
IRFs	Impulse Response Functions
IZA	Institute for the Study of Labour
LLC	Levin-Lin-Chu panel unit root test
MG	Mean Group
MLD	Mean-Log-Deviation
NBSC	National Bureau of Statistics of the People’s Republic of China
OCP	the One-Child Policy
OECD	the Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PIL	Polynomial Inverse Lag
Q-Q	Quantity-Quality
UTIP	University of Texas Inequality Project
VAR	Vector Autoregressive
WIID	World Income Inequality Database

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Abstract

This thesis examines the effects income inequality has on economic growth, drawing on data from China. It focuses on two related questions: whether income inequality is harmful to economic growth and, if so, why.

The first empirical chapter uses a newly-developed panel dataset at the province level to examine the long-run impact of income inequality on economic growth, addressing the problem of spurious regression that affects much of the existing literature. The empirical results indicate that the long-run effect of income inequality on economic growth is non-linear: while income inequality exerts a positive impact on economic growth for rich provinces, it is harmful to economic growth for poor regions.

The second empirical chapter provides mathematical and empirical evidence that demonstrates the deficiencies in existing studies that solely rely on macroeconomic data. It examines three mainstream transmission mechanisms by using data at both the household and village level. At the village level, the empirical results show that income inequality leads to lower economic growth. However, at the household level, income inequality is positively linked to income growth for households with low levels of initial income. Such seemingly contradictory results agree with the predictions of my mathematical example and suggest that the political economy channel is responsible for the inequality-growth relationship in rural China.

The last empirical chapter examines whether inequality and growth are linked across generations by evaluating the impact of the One Child Policy on fertility and education in China. Using a difference-in-differences approach, the empirical results suggest that the One Child Policy successfully lowered the probability of having a child for Han women and increased the probability of attending school for Han children. This empirical evidence indicates that the endogenous fertility channel operates in China.

Chapter 1. Introduction

I think inequality is not a problem per se. I think inequality up to a point can actually be useful for innovation and growth. The problem is, it's a question of degree. When inequality gets too extreme, then it becomes useless for growth and it can even become bad because it tends to lead to high perpetuation of inequality over time and low mobility. ... And also, extreme inequality can be bad for our democratic institutions if it creates very unequal access to political voice, and the influence of private money in U.S. politics.

Thomas Piketty

Income inequality has long been one of the core research interests among economists and sociologists, and sits at the top of the political agenda in many countries around the world. As reported in OECD (2015), the income ratio between the top 10 percent of the population and the bottom 10 percent has increased from 7:1 in the 1980s to 9.5:1 today, reaching its highest level in the past three decades in OCED areas. The potential consequences of this dramatic increase in income inequality are complicated.¹ However, what concerns economists the most is the effect of income inequality on economic growth.

Okun (1975) initially proposed the notion that there may be trade-offs between equality and efficiency, an idea which has been rooted in policymakers' consciousnesses ever since. On the one hand, an important task for economists is to allocate scarce resources in an efficient way, therefore increasing economic efficiency and the size of the 'pie'. On the other hand, such an allocation might involve an uneven (but not necessarily unfair) distribution of resources. It seems that, to some extent, the goal of limiting income inequality and the goal of maintaining a sustainable level of economic growth are contradictory because

¹ These consequences, as discussed in Burtless & Jencks, (2003) and Neckerman & Torche (2007), relate to the phenomena ranging from welfare state, socio-political instability, intergenerational immobility, poverty trap, all of which are tightly linked to our daily life.

redistribution may lead to economic inefficiency and shrinkage of the ‘pie’. However, more recent research tends to suggest that income inequality, at a moderate level, will encourage economic growth and that only extreme inequality will be useless for economic growth, as noted by Thomas Piketty in the opening quote. Sadly, the definitions of ‘moderate’ and ‘extreme’ income inequality are unclear and the related empirical literature has failed to reach a consensus regarding the effects of income inequality on economic growth. The majority of studies run standard growth regressions with a measure of income inequality as an extra explanatory variable with global data (see Alesina and Rodrik, 1994; Persson and Tabellini, 1994; and Clarke, 1995; Forbes, 2000; Barro, 2000). With different estimation techniques and various models, both positive and negative coefficients on income inequality are found.

A major concern with the existing literature is that most focus on global data, ignoring potential heterogeneity across countries/economies. It is not clear that policy makers in one country can rely on the results from other countries. This problem is especially serious after Barro’s (2000, 2008) finding that income inequality has different effects on economic growth between poor and rich countries. Barro’s studies illustrate how failing to take into account a country’s level of development will lead to misleading general conclusions. In the past, it was difficult to conduct empirical research focusing on a single country due to lack of suitable data. However, recently, the development of new surveys and improved methods of generating data, especially on income inequality, makes single-country research possible. In particular, this thesis will use China as a setting in which to look at the inequality-growth nexus in depth.

For scholars who investigate the effects of income inequality on economic growth, China is a seemingly promising laboratory. Since the commencement of economic reform, increasing income inequality is a critical problem in China in the past 30 years. According to the World Bank data, the Gini coefficient in China has increased significantly from 0.3 from 1987 to over 0.42 in 2010.² The Gini

² The Gini coefficient is commonly used to measure the level of income inequality. It ranges from 0 (perfect equality) to 1 (extreme inequality). A Gini coefficient of 0.4 is generally considered as a benchmark for extreme inequality. According to World Bank data, the Gini coefficient of Denmark,

coefficients announced by the National Bureau of Statistics of the People's Republic of China (NBSC) are even higher, peaking at almost 0.5 in 2008, and gradually decreasing to 0.465 in 2016. Even though the degree of income inequality in China is not as high as those in Brazil and Honduras (above 0.55), China is still one of the most unequal 25% of countries of the world. At the same time, the Chinese economy has experienced remarkable development. During 1979 to 2012, the average annual growth rate of gross domestic product (GDP) was 9.8%, compared to a global average of 2.8% during the same period. Although most mainstream theoretical mechanisms suggest that the impacts of income inequality on subsequent economic growth will be negative, these theories might not apply in the Chinese context, given that both the level of income inequality and economic growth rate in China increased dramatically since economic reform.

This thesis addresses two fundamental research questions: is income inequality harmful to economic growth in China? And which transmission mechanism is predominant in explaining the impact of income inequality on economic growth?

The answer to the first question is important for China's policy makers. Although China's central government has realized the importance and urgency of inequality alleviation, a high GDP growth rate is still considered as the highest priority since this is an important measure for assessing the performance of local government by the Chinese bureaucracies. If empirical results show that income inequality is harmful to economic growth, policy makers might be able to maintain a high level of growth and reduce the degree of income inequality at the same time. However, if there exists a positive relationship between inequality and economic growth, growth would need to be sacrificed under any inequality reduction programme.

The first empirical chapter in this thesis (Chapter 3) looks at the long-run effects of income inequality on economic growth in China, drawing on panel time series techniques. Developments in data collection and computation have allowed the investigation of the inequality-growth relationship to evolve from large cross-

a country that is commonly considered as relatively equal, is highest at 0.291 in 2011. Brazil, which is treated as one of the most unequal countries, has Gini coefficients that are consistently higher than 0.5.

section analysis to (dynamic) panel data analysis. However, few researchers have paid enough attention to the issue of spurious regression arising from the time-series properties of the data. Drawing on new inequality data at the provincial level provided by the University of Texas Inequality Project (UTIP), Chapter 3 addresses the spurious regression concerns by employing autoregressive distributed lag models (ARDL). This study is the first to examine the inequality-growth relationship using the ARDL framework. An additional contribution of Chapter 3 is to employ an improved measure of income inequality at the province level, which has not been used in previous studies.

The answer to the second research question is equally important. Authors have put forward several explanations for why income inequality might impact economic growth: the credit market imperfection channel (see, Galor and Zeira, 1993; Banerjee and Newman, 1993); the political economy channel (see, Alesina and Rodrik, 1994; Bertola, 1993; and Persson and Tabellini, 1994); and the socio-political stability channel (see, Alesina and Perotti, 1994; Gupta, 1990; Perotti, 1996). However, there are few studies to support any of these transmission channels with their empirical results. Wrong remedies might be implemented to deal with the trend of increasing income inequality if policy makers do not know how income inequality affects economic growth exactly. For example, if the political economy is predominant, income inequality may retard economic growth in part because the efforts on redistribution caused by the unequal society themselves exert distortionary effects on growth. In this case, taxes and transfers may be thoroughly inappropriate policies (Ostry *et al.*, 2014).

The second empirical chapter (Chapter 4) of this thesis tests the transmission mechanisms underlying the inequality-growth relationship from a special angle. In particular, the existing related empirical literature has not paid enough attention to the potential issues with macroeconomic (aggregated) data and wrongly specified growth functions, which could have exaggerated the negative impacts of income inequality on economic growth (if it indeed exists). The first part of the chapter demonstrates these concerns with both mathematical examples and empirical evidence. The second part of the chapter addresses the second research question by examining three mainstream transmission mechanisms directly, namely, the

political economy, the socio-political instability, and the imperfect credit market channel. The analysis is done at both the village ('macro') and household ('micro') level. Chapter 4 makes two major contributions. Firstly, it illustrates the deficiencies of the existing empirical literature that relies on aggregated data and uses wrong specifications for the growth function. Secondly, it provides a new method of testing multiple transmission mechanisms, which has not been done by any previous study.

In addition to its potential impact on economic growth within a single generation, income inequality might reduce the economic growth of subsequent generations. The endogenous fertility channel predicts that high levels of inequality in one generation will reduce economic growth rate in the next generation due to different fertility preferences between the rich and the poor (see, Galor and Zang, 1997; Morand, 1999; Kremer and Chen, 2002; de la Droix and Doepke, 2003). The last empirical chapter (Chapter 5) builds on the analysis of Chapter 4 and provides an indirect test of the endogenous fertility channel by evaluating the introduction of the One Child Policy in the late 1970s. The One Child Policy was designed to curb the population growth rate and to improve the 'quality' of the next generation. Therefore, if the One Child Policy significantly increased education participation, it is evidence in favour of the endogenous fertility channel. The chapter evaluates the effects of the One Child Policy on fertility and education, treating the introduction of the policy as a huge natural experiment. An innovation of this study is the creation of a retrospective panel dataset reflecting the entire fertility histories of each woman in the sample. Compared to previous studies, this improves the accuracy in identifying the treatment group within the difference-in-differences framework.

Overall, the thesis makes three major contribution. First, examining the transmission mechanisms is difficult especially when the related data is unavailable or unobservable. To concur this difficulty, this thesis is first to provide new method to examine the political economy, the socio-political instability, and the imperfect credit market channel. In addition, taking the advantage of the One Child Policy, this thesis also examines the endogenous fertility channel, even when the inter-generational data is unavailable. Second, it criticises the previous literature that

solely relies on macroeconomic data, providing both mathematical and empirical evidence in favour of using more disaggregated data. Third, apart from the new method, the empirical results of the thesis are mostly based on updated or newly-developed data that aims at mitigating and improving on the data used in the previous literature. The insights from the results that are reported are potentially important for policy makers, as the implications of previous empirical studies – which mostly use aggregated data and do not identify specific transmission mechanisms – might be misleading.

Apart from the current introduction chapter, the remainder of this thesis is organized as follows. Chapter 2 provides a detailed literature review of both theoretical and empirical research on this topic, both at the global level and single-country level. Chapter 3 answers the first research question and Chapter 4 and 5 answer the second one. Chapter 6 concludes.

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Chapter 2. Literature Review

This chapter provides an overview that how the previous literature has approached to the research questions that have been raised in the last chapter. It begins with the introduction of four mainstream theoretical mechanisms: the credit market imperfection, the political economy, the socio-political instability, and the endogenous fertility channel. Then this chapter reviews the related empirical evidence obtained from the data at the global level, and from focusing on one specific country, including China.

2.1 Theoretical Mechanisms

The relationship between income inequality and economic growth has obtained enormous attention among economists since 1950s. Kuznets (1955), the pioneering work, firstly put forward that income inequality increases in the early stage of economic development and decreases in the later phase of economic growth, which is generally referred as ‘inverted U’ hypothesis. If this theory can be applied to the China’s context, ‘inverted U’ hypothesis implies that the level of income inequality will decline with the future economic development. However, Kuznets hypothesis might be invalid in many cases. Deininger and Squire (1998) considered the Kuznets hypothesis is flawed due to problematic cross-country data. By using longitudinal data, Deininger and Squire (1998) show that per capita income does not always change along with changes in inequality in most of countries. They also find that many counties that were initially poor did not experience any increase in inequality while their per capita income grew rapidly.

Since early 1990s, theoretical explanations of the impacts of income inequality on economic growth have grown considerably. Generally, income inequality affects growth through various channels. The mainstream explanations include (1) the imperfect credit market; (2) the political economy; (3) the socio-political instability; and (4) the endogenous fertility.

Credit Market Imperfection

One link between income inequality and economic growth is known as the credit market imperfection channel. Through this mechanism, some previous literature has

concluded that income inequality is harmful to economic growth. The main idea of this mechanism is that poor people would have less opportunity to obtain loans from the credit market due to strict borrowing constraints. If the chance of investment relies on one's level of incomes and wealth, impoverished families, which have limited access to loans, would have fewer chance to invest on both physical and human capital. As Barro (2000) points out, a reallocation of wealth and incomes from affluent individuals to needy ones would improve the productivity of investment.¹ As a result, policies that aim at inequality reduction might improve the investment efficiency and therefore the economic development, which implies a negative inequality-growth relationship.

The pioneering study of credit market imperfection is Galor and Zeira (1993). In this research, they construct an intergenerational framework to explain the relationship between borrowing constraints, the allocation of initial wealth, and total investment level within an economy. In their intergenerational model, individuals are assumed to live for two periods and they can leave bequest for their offspring. In each period, Galor and Zeira (1993) also assume that the only product in the economy could be produced only by employing skilled labour and capital; or by using unskilled labour only. Specially, in the first period, people could choose either to invest in human capital such as receiving education or acquiring qualifications, or to work as an unskilled worker. In the second period, one could be skilled or unskilled labour according to their education level, and could leave a bequest to their children. Also, individuals are supposed to share the same preferences and capacities; the only difference between each other is the initial wealth that they inherited from older generations.

In an imperfect credit market, the cost of monitoring borrowers becomes higher due to asymmetric information, which drives up the interest rate for borrowers. For poor households, if obtaining a loan from credit market is difficult and costly, they are not capable to accumulate human capital and working as unskilled labour. In other

¹ It is worth to note that Barro (2000) explains that if the business involves certain level of set-up cost, then the reallocation of wealth and income enable more poor people to invest, therefore increasing the overall investment and economic growth. However, if the set-up is too high relate to the median income, wealth concentration is needed to meet the investment threshold. In this sense, inequality might be useful for economic growth.

words, only rich people (with large amount of initial inheritance) are able to access education, to become a skilled labour, and to accumulate physical capital. As a result, in the short run, distribution of initial wealth determines the total level of investment and the labour structure of this economy. This theory also holds in the long run. Considering the dynamics of this economy, the inability of human capital accumulation for poor people would lead to a lower amount of inheritance in the next period. If this situation continues generations to generations, Galor and Zeira (1993) put forward that this economy would reach a long run equilibrium with two types of households. The first one is referred as rich dynasties, which implies that all generations in this group will have enough initial wealth to accumulate human capital, then work as skilled labour and leave a large amount of wealth for their offspring. The other type of household is poor dynasties, which means that people within this group will have fewer inheritances, less chances of access to education, and will become unskilled workers. Thus, impoverished families will be caught in a poverty trap, that is, poor people will end up being poor. As a result, if the size of the latter group is sufficiently large, then high initial inequality of wealth distribution will lead to a low level of economic growth.

In the same line, Banerjee and Newman (1993) develop a theoretical framework to analyse the interplay between credit market imperfections and occupational choice.² On the one hand, their research point out that the dynamics of occupational choice could affect economic growth since the decisions of choosing a job could influence the distribution of wealth and income. Then such distribution would have effects on factors (such as savings, and investment) that are closely linked to economic growth. On the other hand, Banerjee and Newman (1993) also put forward that the economic development could conversely influence the occupational pattern within the economy.

Barro (2000) holds a different view in terms of the negative impacts of income inequality on productivity of investment in an imperfect capital market. In his research, he puts forward that if capital markets and legal institution improve with

² This model is different from the one that is proposed in Piketty (1997a), assuming that all the agents are treated as entrepreneurs that only differ in the amount of their investments.

the development of the economy, the overall impacts of inequality on subsequent growth is uncertain because of the offsetting effect derived from the setup cost along with investment. For instance, a business would require a certain amount of setup cost in order to be beneficial and productive. In some cases, Barro (2000) predicts that the reduction of income inequality would also reduce the investment, therefore lower the economic growth.

Political Economy

Another mechanism that could explain impacts of income inequality on economic growth refers to the political economy channel. Most of previous studies (such as Alesina and Rodrik (1994), Persson and Tabellini (1994), and Bertola (1993)), have concluded that income inequality is negatively associated to the subsequent economic growth via two theories, namely, the median voter theorem and the lobby behaviour. The main idea of political economy channel is that highly unequal income distribution would result in a higher tax rate in order to redistribute social resources from rich people to poor ones, which have been named as ‘political mechanism’ in Perotti (1996). Then ‘economic mechanism’ implies that the redistribution and tax policies, in turn, impede economic development through its distortionary impacts on investment and saving behaviour (Perotti, 1996).

Median voter theorem implies that under certain assumptions, the elected result via a majority rule voting system is closest to the median voter’s preference.³ Meltzer and Richard (1981) propose a model with proportional taxation where income distribution is normally asymmetric. Under the majority voting system, the median voter theorem predicts that the elected outcome will represent the median voter’s preference. For this reason, if the gap between the median pre-tax income and the mean pre-tax income, there will be more incentive for the median voter to vote for a higher tax rate on income. They conclude that this redistribution process is

³ There are two key assumptions for median voter theorem. First, voters could clearly place all their given choices on a left-to-right continuum, which makes all the political candidates one-dimensional. Second, the preferences of each voter must be single-peaked, which implies that voters select the political candidates that can represent their will most. Under these two assumptions, the median voter theorem indicates that voters are encouraged to choose the candidates that can best represent their true preference (Downs, 1957).

detrimental to the economic development since it discourages incentive to work, save, and investment.

Alesina and Rodrik (1994) put forward that in a one sector endogenous growth model with productive government spending and different optimal tax rate among agents, median voter theorem in this context implies that the more unequal is distribution in an economy, the lower endowed is the median voter with capital. As a result, it leads to a higher tax rate on capital and a lower subsequent economic growth rate. However, Li and Zou (1988) find out a result that is inconsistent with the negative inequality-growth nexus proposed by Alesina and Rodrik (1994). In Li and Zou (1988), government spending should be divided into production services and consumption services. The latter one should enter the utility function. With this extension, Li and Zou (1988) analyse the impact of income inequality on economic growth in another extreme case, that is, all government spending is used for consumption, which is exactly opposite to the case in Alesina and Rodrik (1994). Li and Zou (1988) also conclude that both extreme assumptions that government expenditure only enters the production function and completely enters the consumption function are not realistic. Considering that the real case should be somewhere between these two extremes, the effects of income inequality on growth is uncertain from their theoretical model.

Apart from median voter theorem, another channel that can be used to explain the inequality-growth nexus within the political economy framework is lobby behaviours. Barro (2000) puts forward that affluent individuals could prevent the redistributive policies via bribery, lobbying, and buying of votes. However, such behaviours would worsen the case and lead to a more unequal inequality in this economy, which in turn requires further political interventions to avoid further redistribution. However, the lobbying or bribery activities could consume resources that should have been put into the productive activities. Hence, even if there is no transfer from the rich to poor in the steady state, a negative inequality-growth nexus could still be obtained through the analysis of political economy channel.

Socio-Political Instability

Other researchers have stressed that income inequality affects economic development through socio-political instability. Under a highly economic polarized economy, the return outside from the normal market activities tends to be higher. For this reason, Alesina and Perotti (1996), Perotti (1996), and Acemoglu and Robinson (2001) argue that unequal income distribution generates strong motivations for people, who pursue their interests, to engage in rent seeking activities and social disrupting behaviours such as revolution, crimes, or coups. Based on this argument, more studies have focused on the adverse effect on socio-political instability on the total level of investment, and economic growth. Alesina and Perotti (1996) point out that socio-political instability could adversely affect investment for at least two aspects. First, it generates uncertainty in terms of the legal and political environment. As a result, total investment would be lower since people who are risk averse would postpone their projects or invest in other countries with less uncertainty. Second, disruptive activities such as riots and crime interrupt the normal market order and therefore lower the productivity. This argument is also supported in Barro (2000) by stating that antisocial actions or social conflicts induce a direct waste of resources, the resources that should have been devoted to productive activities.

Benhabib and Rustichini (1996) provide a game-theoretical framework to show the interplay between levels of wealth, socio-political instability, and motivation for capital accumulation. They conclude that inequality is adversely affecting economic growth at any given level of wealth.⁴ These authors state that the interest groups in the unequal economy would capture a larger share of total output by direct appropriation or by controlling political system. If the degree of income inequality is too severe, individuals in the disadvantaged position would exert redistributive pressures and discourage capital accumulation, leading to an underinvestment equilibrium. Specially, this effect could be even stronger in poor countries with low level of wealth.

⁴ Benhabib and Rustichini (1996) measure inequality by using the disparity of consumption rate and welfare levels.

Focusing on another game-theoretical model, Rodrik (1999) emphasizes that the differences of economic performance can be explained by the reaction of the domestic social conflicts. In his model, it is assumed that two groups have equal share of the resource. Then they should choose ‘cooperative’ or ‘fight’ to jointly determine the redistribution of the shrunk output due to the external shocks. They would receive equal share of the reduced resource if both groups choose cooperative. Alternatively, they could choose to fight and retain the previous benefit before the shocks. Under this framework, social conflicts will occur if the agents reject to cooperate with each other to share the shrunk pie of economy, which leads to the magnification of the cost of the external shocks as well as the further shrink of the available resource stock.

Endogenous Fertility

Last but not the least, endogenous fertility channel has been put forward as one main explanation to reveal the impacts of income inequality on subsequent economic growth (Galor and Zang (1997); Morand (1999); Kremer and Chen (2002); de la Droix and Doepke (2003)). Assuming income is positively associated to one’s educational level, families with higher income level (or higher educational background) will normally prefer less children and invest more on each child because the opportunity cost of child rearing is too high for them. As time goes by, the children who are invested more from the affluent households are more likely to become skilled labour and to earn much more, then they will choose less children due to the same reason, the high opportunity cost of taking care of children. On the other hand, poor families will choose more children and with fixed income, they can only invest little per child. A vicious circle can be generated when the poor children enter the labour market as unskilled workers and earn tiny salaries. Then again, with various reason apart from low opportunity cost, these adults from the poor families will choose more children who will be unskilled labour in years later.

⁵ In an unequal economy, at the macro level, the aggregate level of human capital

⁵ Apart from lower opportunity cost of rearing children, for the poor, choosing more children can also be motivated by insufficient old-age-support (Khoo and Dennis (1999); Morand (1999)), low education return (Dahan and Tsiddon (1998)), and capital market imperfection (Galor and Zang (1997)).

will be diluted due to the increasing proportion of unskilled labour, therefore impeding the economic growth.

2.2 Empirical Evidence

Over the past twenty years, along with the explosion of the theoretical research on the inequality-growth nexus, there are considerable empirical studies have been developed. Despite of the variation of selected data source and indicators of inequality, traditional empirical studies, such as Alesina and Rodrik (1994), Persson and Tabellini (1994) and Clarke (1995) consistently conclude that the impact of inequality on economic growth is negative. More recently, with the introduction of the improved dataset and latest panel estimation, some researcher such as Forbes (2000) and Barro (2000) challenge the previous empirical evidence. However, in spite of an enormous strand of empirical literature on this topic, economists still fail to reach any consensus on the impacts of inequality on growth so far. Several reasons have been suggested to explain the variation of empirical results, such as problematic quality of data, or appropriateness of model specification. This subsection provides a review of the empirical studies on inequality-growth nexus, beginning with the description of the traditional as well as the current state empirical evidence at the international level, complemented by a detailed discussion of the empirical evidence focused on the regional data.

Evidence from Studies Focusing on Cross-Sectional Data

Pioneering empirical research including Alesina and Rodrik (1994), Persson and Tabellini (1994) and Clarke (1995), and Perotti (1996), initially focus on reduced form estimations of the direct impact of inequality on future growth prospects by employing cross-country data. In general terms, these studies commonly regress a measure of economic growth rate on a measure of inequality and on a set of other explanatory growth-driven variables through a linear Ordinary Least Squares (OLS) estimation.⁶ The research interests of these literatures are the sign of the coefficient of inequality and its statistical significance. Despite the difference in data source of income distribution, indicators in measuring inequality, and selected time periods,

⁶ These variables include a measure of initial output level, of human capital stock, physical capital investment ratio, and regional dummies, the variables which have been proven to be significant determinants of economic growth in Barro (1991).

including Alesina and Rodrik (1994), Persson and Tabellini (1994) and Clarke (1995), and Perotti (1996) consistently obtain significant and negative coefficients on inequality variables, implying that inequality is detrimental to growth in the long run. In addition, by splitting up the sample into different categories, Persson and Tabellini (1994) put forward that the negative impacts of inequality on growth are only significant in democratic countries, whereas Perotti (1996) obtains a result that adverse effect of inequality on growth only exists in rich countries.

By the late 1990s, other economists criticized the general consensus on the negative relationship between inequality and growth since this relationship is invalid when other econometric techniques or dataset have been used. Through the analysis of the more recent literature, the major concerns of the pioneering empirical research can be concluded as the quality of data on income distribution, data comparability among countries, estimation techniques, and the model specification that is employed to capture the impact of inequality on growth.

According to Knowles (2005), majority of the previous existing empirical research on exploring the impact of inequality on growth suffer from two main potentially serious data issues, namely the data quality and the data comparability. The first data problem has been emphasized by Deininger and Squire (1996). These authors argue that the data set on income distribution that allows comparison across countries should meet the minimum quality standards. They require that, data on inequality should be based on household surveys, rather than the information drawn from the national account statistics; observation must not only cover wages, but also cover all sources of income including nonmonetary ones; coverage of the observation should be representative of the whole population at the national level, rather than dealing with, for instance, the urban residence or taxpayers only. Based on these criteria, Deininger and Squire (1996) assemble an improved dataset that contains 682 (out of 2600) qualified observations, the dataset which has been kept employing by some empirical research thereafter. Furthermore, in their following empirical work, Deininger and Squire (1998) find out that some of the 'unqualified' observations have been used in the traditional empirical studies. For instance, Deininger and Squire (1998) point out that only 18 of 55 observations in the dubious dataset that used in Persson and Tabellini (1994) could meet their

minimum standard. Using their own high-quality dataset, Deininger and Squire (1998) find out a negative relationship between initial income inequality and subsequent economic growth. However, this relationship is not robust when the regional dummy variables are introduced.

Apart from the quality of data, another potential data deficiency of previous studies is data incomparability. Knowles (2005) emphasizes that majority of the empirical investigation on the inequality-growth nexus does not measure income inequality in an identical manner. She stresses that the mixed non-comparable inequality indices that have been used in cross-country studies might be based on various income definitions (net income, expenditure, gross income) and on different survey unit (individuals or household). One example is that the distribution of income after tax should be more equal than the one measured before tax under the progressive tax system. Another example stressed in Fields (1994) is that the distribution of income is supposed to be less equal than the indices based on expenditure if the individuals (or households) allocate their resource more evenly over their life time. Therefore, without enough consideration of data comparability, these discrepancies may result in serious data problems when combining income data across countries.

Empirically, Knowles (2005) points out that there is no empirical evidence of a significant relationship between income inequality and economic growth once the income inequality indices are consistently measured as gross income, which challenges the general consensus on negative inequality-growth nexus. However, when income inequality is identically captured by the expenditure data, Knowles (2005) obtains strong evidence supporting that the impact of income inequality on growth is negative.

Another main concern of the traditional consensus on negative impact of inequality on growth is limitation of econometric estimation techniques. One main drawback of the studies employed cross-country estimation techniques is that the estimation results might be biased due to the neglect of time-invariant country specific variables. Forbes (2000) argues that potential bias on estimation could be derived from omitted country specific variables that have significant impacts on growth and inequality at the same time, but in the opposite direction, for instance, corruption and fertility rates. Moreover, Deininger and Squire (1998) also suspect that

previous cross-country studies suffer from omitted variable bias from the evidence that the significance of inequality coefficient would be dramatically weakened once regional dummy variables are included.

The introduction of the high-quality dataset provided by Deininger and Squire (1996), or its subsequent extensions (e.g. the World Income Inequality Database (WIID)), has allowed economists to examine the relationship between income inequality and growth with panel estimation methods such as fixed effects and general method of moments (GMM). These new econometric techniques, by controlling the unobserved fixed-effects, have the important advantage of eliminating time-invariant effects that might cause the omitted variable bias. The first set of empirical papers that have used panel data estimation techniques include Li and Zou (1988) and Forbes (2000). The latter study employs fixed effects, random effects, and first-differenced GMM to estimate the growth regression that has been used in Perotti (1996). The empirical results in Forbes (2000) show that the coefficients on the income inequality variable are never negative, implying that an increase in income inequality has a significant and positive effect on the economic growth in the short term. In the same line, Li and Zou (1988) also obtain positive coefficients on income inequality in fixed effects, random effects, and even in all sensitivity analysis, suggesting that in the short-run income inequality encourages the subsequent economic performance. Similar evidence also could be found from the empirical studies that are focusing on one country. Partridge (1997) and Panizza (2002) obtain different signs on inequality when they both examine state-level data within the United State of America. Panizza (2002) therefore conclude that tiny differences either in data or in the selected methodology between inequality and growth would generate significant different results.⁷

Different in model specifications that have been used to capture the impacts of inequality on growth would also bring about the opposite results. Barro (2000) states that the relationship between income inequality and economic growth might not be linear and this argument has been supported by his empirical evidence. He

⁷ It is worth noting that the estimation techniques used to examine the inequality-growth nexus are not the only difference between Partridge (1997) and Panizza (2002).

estimates a system of equations with instrument variables to explore the impacts of initial level of income inequality on the average growth rate of a broad panel of countries over successive spell of ten years covering from 1965 to 1995. When estimating with the whole sample, the empirical results that are obtained from three-stage least squares estimation reveal that the coefficient on income inequality is close to zero, implying that the relationship between initial inequality and economic growth is weak. However, considering that the Gini coefficient is allowed to depend on the level of economic development, Barro (2000) finds that the impacts of income inequality on growth is negative in the poor countries, and is positive for the rich ones, therefore suggesting a non-linear relation. This relationship has been confirmed by his recent research, Barro (2008), with an improved dataset, World Income Inequality Dataset (WIID).

Evidence from Studies Focusing on One Country

There are some problems that are still needed to be resolved. Foremost, due to the issue of data unavailability, especially for the income distribution data, majority of existing empirical studies have been forced to employ the averaged data that include large amount of countries in order to increase the sample size. Apart from the issue of data incomparability as pointed out by Knowles (2005) and Partridge (2005), another potential problem of this practice is that the same model specification might not be applied to all countries due to heterogeneity. For instance, Partridge (Partridge, 1997) states that the data have been used in Persson and Tabellini (1994) include Chad and United States, the countries which are in every different stage of economic growth. In this case, the estimated results might represent an average relationship that does not validate equally for the rich countries and poor ones. Banerjee and Duflo (2003) point out that one deficiency of the data set at the international level is derived from the differences in national characteristics such as cultural background, population, and financial institutions. This argument is also supported by Frank (2009). He argues that the heterogeneity of the structural differences across international panels, such as corruption levels, education system, type of economy, etc, might be more likely to contribute to omitted variable bias.

The second problem is due to the practice of averaging data to test the relationship between income inequality and economic growth. Subject to the difficulty to collect the successive data on income distribution (or other explanatory variables), one common way to construct a panel data set is to divide the time belt evenly into several intervals and calculate its mean value. However, this practice is not without its drawbacks. On the one hand, Wan *et al.* (2006) emphasize that the division of the time horizon would be a pure guesswork since there is no consensus regarding the definition of short-, medium-, or long-term. For instance, some economists might consider a 10-year period as short run, whereas other researchers think this would be long enough to be a medium term. On the other hand, the conventional averaging process might be problematic since it is possible that conflicts results could be obtained from two different ways of time division. For example, Forbes (2000) obtains a positive effect of inequality on economic growth in the short-run (over 5-year intervals), whereas the inequality-growth relationship is not significant while the author employed the 10-year intervals.

To resolve the abovementioned problems with the empirical research at the international level, some economists start to explore the relationship between income inequality and economic growth by narrowing the research scope to one country. The motivation of such type of empirical research is threefold. First, one key advantage of using regional data instead of the international ones is that states (counties or provinces) should share similar features such as education level, government expenditure, which would be more reasonable to use the same specification. Second, as Panizza (2002) suggests, one possible solution to deal with the data incomparability issue is to use the regional data, which is more like to be measured in a consistent manner. Third, limiting the scope of the research to regions within the same country/economy could provide policy makers with more straightforward evidence of inequality-growth nexus rather than the general conclusion obtained from the global data. Nevertheless, given the advantages listed above, the related literatures on regional level are relatively scarce due mainly to the data unavailability problem.

By using the U.S. state level data, Partridge (1997) supports a positive relationship between income inequality and economic growth.⁸ Based on the panel estimation (fixed effects, differenced-GMM, and system-GMM) with U.S. state level data from 1940 to 1980, Panizza (2002) could not find the presence of a positive inequality-growth nexus as proposed in Partridge (1997). Furthermore, he points out that the empirical result of inequality-growth nexus is sensitive since tiny changes in the method of measuring inequality, and in the econometric model could generate enormous differences in the estimated results. Via the panel error correction estimators: the fixed effects estimator, the mean group (MG) estimator of Pesaran and Smith (1995), and the pooled MG estimator of Pesaran, *et al.* (1999), Frank (2009) finds a positive long run relationship between inequality and growth with large and balanced size of dataset covering state level data from 1945 to 2004 on annual basis. Frank (2009) also uses various measure of inequality (such as Atkinson index, and Theil entropy index) and concludes that such positive inequality-growth nexus might be mainly caused by the income concentration within the upper end of the income distribution.

Nahum (2005) and Cialani (2013) provide relevant empirical evidences by focusing on the Swedish case. The former study investigates the relationship between income inequality and economic growth based on county level data for Sweden covering from 1960 to 2000. Nahum (2005) considers both annual data and averaged information as well to test the appropriateness of averaging data. By using fixed effects and two-stage least squares (2SLS) estimation, she finds a significant positive partial correlation between Gini coefficients and economic growth on in the cases of yearly data, averaging by 3-year interval, and averaging by 5-year interval. However, the corresponding impacts of Gini coefficient on economic growth averaged on 10-year is proved to be not significant. The latter study supports this positive relationship with a new data set at the Swedish municipal level covering from 1992 to 2007. Via the fixed effects and 2SLS estimation, Cialani (2013) regresses economic growth (measured by growth rate of average income) on a set of explanatory variables including the initial level of average

⁸ Partridge (1997) measures income inequality by Gini coefficient and by income share of the middle quintile. The coefficients on both measures are positive and statistical significant.

income, a measure of initial level income inequality, and other growth-driven factors.⁹ The author concludes that the income inequality in Sweden (measured by Gini coefficient or top income share) is positively correlated to the income growth. Specially, allowing the income inequality could be depended on the municipal income level, Cialani (2013) also points out that the income inequality would encourage the economic growth in the municipalities with higher average income level. In conclusion, in the case of Sweden, both studies considered the share of age groups in the adult population as instrumental variable for the income inequality when they used 2SLS estimation. Furthermore, taking the advantage of the data availability on income distribution, both research try to measure the inequality in different ways (such as income share of top 1%, 5%, 10%, 25%) or to test the regression in different ways of averaging data (such as 10-year, 5-year, and 3-year), concluding a positive inequality-growth nexus in Sweden.

Ghosh and Pal (2004) collect the state-level data covering from 1960 to 1994 in India to test the relationship between inequality and economic growth via simple cross-sectional OLS estimates and panel data estimation. In the OLS estimation, these authors regress the growth of per capita state domestic product on initial level of income, the rural Gini, urban Gini, intersectoral inequality component, a measure of human capital, and a measure of physical capital, prevailing in the initial period 1960. They find out that the impacts of rural inequality on growth are significantly negative while the effects of urban inequality were insignificant positive.¹⁰ Also, the coefficient on the intersectoral inequality index is significantly negative, which they suspect that this might be caused by ignoring the state-specific characteristics. To deal with this potential concern, Ghosh and Pal (2004) then employ fixed effects estimator, concluding that both rural Gini and intersectoral inequality component are significantly and negatively associated with the subsequent economic growth

⁹ It is worth noting that the explanatory variables that have been used in Nahum (2005) and Cialani (2013) are different from the traditional specifications that have been used in the related studies at the international level. In Nahum (2005), the author controls for the urbanization and the age structure, the stock of human capital, the initial level of income per capita, and a measure of income inequality. By contrast, Cialani (2013) employs the share of expenditure on education, child care, family care, and elderly care, respectively, a measure of inequality, stock of human capital, and political stability as explanatory variables.

¹⁰ Gini coefficients that have been used in Ghosh and Pal (2004) are based on consumption inequality instead of income inequality.

whereas the urban Gini still fail to exert significant effects on growth.¹¹ The main conclusion of their study is that the rural inequality discouraged the subsequent economic performance while the urban inequality have no impacts on growth.

The empirical work on exploring the relationship between income inequality and economic growth in China is even fewer. One main obstacle of the developing relevant literature is that related data, especially on income distribution, is unavailable due to the political reasons. Even though the National Statistics Bureau of China has published some Gini coefficients, the need for more informative data is urgent for research purpose.¹² Extending the work of Forbes (2000) and Lundberg and Squire (2003), Wan *et al.* (2006) explicitly estimate the inequality-growth nexus in the short and long run. These authors introduce the polynomial inverse lag (PIL) framework to the simultaneous systems of equations to deal with the reverse causality from economic growth to income inequality.¹³ In addition, since Wan *et al.* (2006) criticize the practice of averaging data in the previous literature such as (Forbes, 2000), another motivation to employ PIL framework is the flexibility in exploring the true lag structure, which enabled the identification of the impacts of inequality on growth on different time horizons. By using the provincial panel data covering from 1987 to 2001, they find out that income inequality (measured by the income ratio between the urban and rural resident) discourage economic growth irrespective of time horizons. Through the system estimation, Wan *et al.* (2006) also point out that the positive effect of inequality on human capital is overtaken by the negative effects of income disparity on physical investment. Chen (2010) employs a vector-autoregressive (VAR) model and simulated the effects of shocks to the growth and Gini coefficient by analysing the impulse response functions (IRFs). After confirming the stationarity of both of inequality and growth, he concludes that increase in economic growth discourage inequality in short run and long run. Also, the author also puts forward that a lower

¹¹ Due to the missing data on Gini indices for certain years, Ghosh and Pal (2004) divide the whole sample into seven subperiods based on a 5-year interval.

¹² National Statistics Bureau announced the national Gini coefficient from 2003 to 2012 on January 2013, and from 2013 to 2016 on January 2017.

¹³ Wan *et al.* (2006) propose a system that contained four reduced form equations. Apart from income inequality and economic growth proxies, these authors also endogenize the human capital variables and investment.

economic growth will be accompanied by reducing inequality in the short run, and such effects would disappear in the long run. With the household-level data, Benjamin *et al.* (2011) also find out that the negative impacts from inequality to growth fade away by the end of observed time period. Other literature calculate Theil index based on data at city level (Reuter, 2004) or at prefecture level (Gravier-Rymaszewska, et al., 2010), finding positive impacts from income inequality on economic growth rate in China.

2.3 Concluding Remarks

To answer the two research questions that have been proposed in the beginning, this chapter provided a general review of the theoretical and empirical literature regarding the effects of income inequality on the subsequent economic growth. On the theoretical side, this chapter mainly reviews four transmission mechanisms, namely, the credit market imperfection, the political economy, the socio-political instability, and the endogenous fertility channel. One should note that the list of the transmission mechanisms is longer than what have been discussed in this chapter. For example, the adverse effects of income inequality on economic growth might through the transmission mechanism of lobbying, corruption and misallocation of resources (see, Barro 2000; Easterly, 2001; Fogel, 2006; Galor *et al.*, 2006), or the channel of small size of demand (see, Zweimuller, 2000; Foellmi and Zweimuller, 2006). However, this thesis will only focus on the empirical analysis with the channels that have been discussed in detailed in this chapter, considering the relevance of the channel itself and the availability of the data. For instance, although the increasing level of corruption is also a concern in China, due to the unavailability of the measure of corruption, the related research is beyond the scope of this thesis. Anything that have not been discussed or tested should count for the limitation of this work rather than denying their importance in the field.

On the empirical side, this chapter reviews the econometrics estimates of the impacts of income inequality on subsequent economic growth from global data to regional data, from cross-sectional techniques to dynamic panel data estimation methods. Although the empirical results do not reach a consensus on the impacts of income inequality on economic growth, the one thing that could be learnt from this literature review is that the estimation results could change significantly depending

on the estimation techniques, the quality of the data, or even the sample that have been chosen. It is worth to note that several aspects that are not paid enough attentions. First, among the all the empirical works, when the economic growth and income inequality are in different integrated orders, the potential spurious regression are rarely discussed. Second, the examinations of the related transmission mechanisms, particularly focusing on regional data, are rare. Hence, to answer the research questions, this thesis will investigate the impacts of income inequality on economic growth specifically focusing on a superior estimation technique (Chapter 3) and on new methods to identify the discussed transmissions (Chapter 4 and 5). Admittedly, other concerns are equally important, which should also be the future research direction in this filed.

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Chapter 3. Long-Run Effects of Income Inequality on Economic Growth: A New Insight from China

3.1 Introduction

Since the commencement of economic reform, increasing income inequality is a critical problem in China in the past 30 years. According to the World Bank data, the Gini coefficient in China has increased significantly from 0.3 from 1987 to over 0.42 in 2010, exceeding the international warning level.¹ The Gini coefficients announced by the National Bureau of Statistics of the People's Republic of China (NBSC) are even higher, peaking at almost 0.5 in 2008, and gradually decreasing to 0.465 in 2016.² Even though the degree of income inequality in China is not as high as those in Brazil and Honduras (above 0.55), China is still one of the most unequal 25% of countries of the world. At the same time, the Chinese economy has experienced remarkable development since 1978. During 1979 to 2012, the average annual growth rate of gross domestic product (GDP) is 9.8%, which is significantly higher than the global averaged rate of 2.8% during the same period.³ Although most of mainstream theoretical mechanisms suggest that the impacts of income inequality on subsequent economic growth is negative, these theories might not be applied in the Chinese context, given the fact that both the level of income inequality and economic growth rate in China increased dramatically since economic reform.⁴ The research question of this chapter is to empirically investigate the overall impact of income inequality on economic growth in the Chinese context using macroeconomic data.

¹ The Gini coefficient is commonly used to measure the level of income inequality. It ranges from 0 (perfect equality) to 1 (perfect inequality). A Gini coefficient of 0.4 is generally considered as a benchmark for extreme inequality. According to World Bank data, the Gini coefficient of Denmark, a country that is commonly considered as relatively equal, is highest at 0.291 in 2011. Brazil, which is treated as one of the most unequal countries, has Gini coefficients that are consistently higher than 0.5.

² NBSC releases the latest national Gini coefficients only from 2003 to 2016. They are 0.479 (2003), 0.473 (2004), 0.485 (2005), 0.487 (2006), 0.484 (2007), 0.491 (2008), 0.490 (2009), 0.481 (2010), 0.477 (2011), 0.474 (2012), 0.473 (2013), 0.469 (2014), 0.462 (2015), 0.465 (2016).

³ The raw data are derived from World Bank and computed by the author.

⁴ As been discussed in the literature review chapter, the mechanisms that suggest the income inequality is harmful to economic growth include the imperfect credit market, the political economy, the socio-political instability, and the endogenous fertility.

Although the China's central government has realized the importance and urgency of inequality alleviation, a high GDP growth rate is still considered as the highest priority since GDP growth rate is still an important measure for assessing the performance of local government by the Chinese bureaucracies. If the empirical results show that income inequality is harmful to economic growth, the policy makers could maintain high level growth and reduce the degree of income inequality at the same time. Otherwise, economic growth should be sacrificed with the inequality reduction if there exists positive inequality-growth nexus.

The relationship between income inequality and economic growth in China has obtained enormous attention among economists. Wan *et al.* (2006) employ the income ratio between urban and rural resident as a measure of income inequality and conclude that the income inequality is negatively associated to the long-run economic growth. By using the same inequality indicator, Chen (2010) finds out that a reduction in inequality has a marginal negative impact on growth in the short run.⁵ Similarly, with the household-level data, Benjamin *et al.* (2011) also find out that the negative impacts from inequality to growth fade away by the end of observed time period. Other literature calculate Theil index based on data at city level (Reuter, 2004) or at prefecture level (Gravier-Rymaszewska, et al., 2010), finding positive impacts from income inequality on economic growth rate in China.

The novelty of the current empirical research is two-fold. First, I will use an improved measure on income inequality, Theil index assembled by University of Texas Inequality Project (UTIP), in hope of mitigating the data issues in previous studies. One advantage of Theil index is that it can be calculated with aggregate (or group-level) data. This calculation requires that the subgroups of a population should be categorized into mutually exclusive and completely exhaustive groups. However, Theil index calculated with geographical sub-province data, such as Chinese city data (e.g., Reuter (2004)) and prefecture data (e.g., Li and Xu (2008)), is less ideal. Due largely to the upgrading of county-seat towns into county-seat

⁵ Chen (2010) also employs the Theil index at the national level as a measure of income inequality, calculated by GDP per capita at the province level.

cities, the number of cities are increasing over time, leading to data inconsistency and incompleteness in related regional Statistics Yearbook. When calculating the Theil Index, this data incompleteness concern violates the completely exhaustive groups requirement, which lowers the quality of the measure of income inequality.⁶ By comparison, since the number of sectors are unlikely changing over time, UTIP Theil index calculated with sectoral information tends to be less problematic. Another superiority of UTIP Theil index is that it employs wage data instead of GDP per capita as a measure of income. When computing the income inequality index, with less ideal data, previous literature that have employed the regional GDP as a proxy for income. However, according to an IMF report (Callen, 2017), GDP sums the incomes generated by production, including not only wages, but also profits, rent, taxes less subsidies. As a result, GDP overestimates the income level and introduces measurement error in the income inequality index. Compared to GDP, sectoral wage data reflects income information more directly.

Second, I will use two newly proposed models by Chudik *et al.* (2013c), namely cross-sectionally augmented autoregressive distributive lag model (CS-ARDL) and cross-sectionally augmented distributed lag model (CS-DL), to investigate the long-run impacts of income inequality on economic growth, in hope of dealing with the econometrics challenges that have not been solved in the previous literature. In particular, from an econometric point of view, there are at least three major concerns in existing related empirics: spurious regression due to non-stationarity process in the regression, cross-sectional dependence (CSD), and slope heterogeneity. Ignoring any of these concerns would lead to severely biased estimation when examining the impacts of income inequality on economic growth in the long run. However, the traditional dynamic panel data approaches that have been used in existing empirics (as in Forbes (2000), Lee and Zou (1998)), including Fixed Effects estimator (FE), and Arellano and Bond (1991) estimator, cannot address any of them. Instead, given the great features of allowing mixture of different stationary processes of variables, heterogeneity slopes and adjusting the

⁶ It is worth to note that the increase of administrative unit (such as county or city) itself is not detrimental to the measure of income inequality with Theil Index. The concern will be arisen while the data is incomplete. Unfortunately, the data incompleteness in regional level is not uncommon, especially in early 1990s. For this reason, Reuter (2004) has to reduce the selected city only to 215 (out of 662 cities in 2011).

cross-sectional dependence, the CS-ARDL and CS-DL together with the Mean Group (MG) estimator that will be employed in this chapter are superior to the pervious methodologies, providing a more reliable estimation regarding the long-run effects of income inequality on economic growth. To the best of my knowledge, this is the first study releases the assumption of slop homogeneity and cross-section independent to investigate the inequality-growth nexus in the Chinese context. In the subsequent chapters, all the mentioned econometric concerns and new methodologies will be further discussed.

3.2 Data

Measuring Income Inequality and Economic Growth

Among the most common metrics used to measure income inequality are the Gini coefficient, Theil index, and Mean Log Deviation (MLD). They have all desirable properties that are postulated to define a proper measure on inequality, namely, anonymity, scale independence, population independence, and transfer principle. This chapter aims at providing new empirical evidence on the relationship between income inequality and economic growth by employing a new dataset on income distribution at the China's provincial level, which is assembled by UTIP. The UTIP measure of China's inequality is mainly based upon Theil index, which is equal to the sum of Theil elements for every subgroup as shown in the following equation.

$$Theil = \sum_{i=1}^m \left\{ \left(\frac{p_i}{P} \right) * \left(\frac{y_i}{\mu} \right) * \ln \left(\frac{y_i}{\mu} \right) \right\} \quad (3.1)$$

where m is the number of subgroup in the population; p_i is the population of subgroup i ; P is the entire population; y_i corresponds to the mean income in group i while μ is the average income within the whole population. Under perfect equality, the last term of equation 3.1 becomes zero, leading to the value of Theil index is zero. If one individual (or group) occupies all of income, the maximum value of Theil index, $Theil = \ln m$, is obtained.⁷ UTIP uses wage and employment data

⁷ It is worth to note that the first product in the equation 3.1, $\frac{p_i}{P}$, could lead to a relatively small value of Theil Index, especially when there are many groups with smaller population. The scatter plot of the Theil Index against the provincial GDP growth could be found in the Figure 3A-1 in the Appendix 3A.

from various issues of annual China Statistic Yearbook. The employment data are derived from the total number of staffs and workers at year-end, while the income data refers to the total wage bills for these staffs and workers before tax and other expenses are deducted. Due to the availability of related employment and wage data, the Theil index assembled by UTIP covers only from 1987 to 2012 for 31 provinces.

The major motivations for using UTIP Theil index is threefold. First, instead of finding a geographical sub-province data, UTIP employs sectoral data which is more practical compared to the data at city or prefecture level. This advantage is of importance in this study. Due largely to the upgrading of county-seat towns into county-seat cities, the number of cities are increasing over time, leading to geographical data inconsistency and incompleteness in related Statistics Yearbook. Second, unlike previous literature, the calculation of provincial Theil index in UTIP adopts the wage data rather than the regional GDP per capita for measuring income information, which offers a closer measure of income inequality. Third, to the best of my knowledge, UTIP inequality data covers the most provinces (31 provinces) and longest time span (26 years) on an annual basis, enlarging the size of total observations.

Regarding economic growth, as some studies use logarithmic real GDP per capita (such as Herzer and Vollmer (2012), and Simões (2012)), I will use first-difference of logarithmic real GDP per capita to proxy economic growth, in line with the growth empirics such as Huang and Yeh (2012), and Barro (2000). One concern that stops Herzer and Vollmer (2012) from using first-difference indicator is that spurious regression would be generated because they argue that first-difference GDP is commonly a stationary process, whereas inequality or other variables are not. However, even this concern might be the case, new econometric models (such as ARDL model) and new estimators (such as mean group (MG) estimator) can tackle with the regression including both stationary and non-stationary processes. In addition, if the logarithmic real GDP per capita should be in place, it will be more likely to explore the relationship between economic development and income inequality, which does not match my current research question.

Measuring Other Variables

Apart from income inequality and economic growth, other two key variables are a measure of physical capital, and a measure of human capital. Particularly, education is a measure of human capital, which has been treated as one of the most important growth determinants among previous growth literature. Theoretical literature (such as Romer (1990)) point out that the major contribution to research and development that promotes technologies is human capital. Its role of ordinary as well as intellectual input into productive activities exerts stimulating effects on economic development (Mankiw, *et al.*, 1992). In addition, investment has been commonly considered as a measure of physical capital. Based on the neoclassical model (Solow, 1956), in a closed economy, the saving rate is exogenous and equivalent to the ratio of investment to output. A higher saving rate drives up the steady-state level of output per effective worker and therefore enhances the economic performance with a certain initial level of GDP. Empirical evidence at the international level (such as Barro (1991), Levine and Renelt (1992)) or at the national level (such as Chen (2000)) also reveal the positive effects of education and investment on the economic growth. According to these theoretical predictions and empirical experiences, it is reasonable to expect that investment and education are growth stimulator.

To measure investment, I will employ the investment-GDP ratio, which is computed as total fixed capital investment over regional nominal GDP.⁸ Following the growth empirics from Chen and Feng (2000), and Wan *et al.* (2006), I will use higher education enrolment rate as the indicator for measuring education. Unless indicated otherwise, the provincial annual data of these variables are derived from the NBSC dataset. The length of the period chosen is dictated by the data availability on inequality data, which covers from 1987 to 2012. In total, I have twenty-nine provinces ($N = 29$) and twenty-six years of data ($T = 26$), for a total of 754 observations.⁹ This dataset, with detailed sources, definition, means, and

⁸ The inflation effect will be cancelled out since both GDP and fixed capital investment are measured in the nominal term.

⁹ This study eliminates the data from Chongqing and Tibet for the following reasons. First, the related data of Chongqing do not available until 1997 when Chongqing officially became a direct-controlled municipality. Second, part of real GDP per capital for Tibet province cannot be calculated since the CPI data does not exist from 1987 to 1989.

standard deviations for each of the variable is listed in the Appendix Table 3A-1. In addition, a plot of the dependent variable, economic growth for each province is also provided in the Appendix Figure 3A-1.

From an empirical perspective, other factors, other than the measures of physical capital and human capital indicated by the neoclassical growth model, could also have impacts on economic growth. For example, Nahum (2005) controls for the urbanization and the age structure in the reduced form growth regression. Cialani (2013) also employs a measure of political stability as a regressor. However, this chapter will only focus on the measure of income inequality, physical capital, and human capital. Although the sample size is the largest compared to the previous Chinese growth empirics, there will be trade-offs between avoiding omitted variable bias and keeping a parsimonious model. Particularly, the inclusion of more independent variables will be significantly detrimental to the estimation with CS-ARDL and CS-DL model due largely to the huge loss of degrees of freedom.¹⁰ Hence, the future research could improve the model by including more exogenous variables that could affect economic growth, if more relevant data are available.

3.3 Potential Econometric Issues with Panel Time Series Data

Majority of previous empirical research focusing on inequality-growth investigation can be characterized as ‘micro panel analysis’ or ‘longitudinal panel analysis’ since the time span is relatively short (less than 10 periods in time dimension). By comparison, the dataset that will be used in this study contains annual data spanning from 1987 to 2012 ($T=26$), which can be normally classified as ‘macro panel analysis’ or ‘panel time-series analysis’. The length of time span is of vital importance because the general estimators (such as FE estimator, and difference-GMM estimator) that have been used in micro panel analysis are not valid for panel time-series analysis. With a longer time span, several potential econometric concerns should be considered, namely, non-stationarity, slope heterogeneity, and cross-sectional dependence (CSD).

¹⁰ This will be discussed in the empirical result subsection in detailed. Particularly, when I include only the measure of income inequality, physical capital and human capital, there are insufficient observations already with the CS-ARDL model (Table 3-4), and CS-DL model (Table 3-5).

Potential Issue 1: Non-stationarity

Short-periods averaged panels (for example, 5-year intervals) has become a standard practice in growth-inequality nexus empirics in the hope of mitigating the uncertainty induced by business cycle, and of dealing with the related data scarcity (such as inequality, and education attainment), without any concern on the time properties of data itself. However, other studies point out that it is reasonable to treat the variables such as the level of gross output or capital stock as ‘non-stationary’ series because these variables often show high degrees of persistence in the long term (Bai and Ng (2004); Pedroni (2007); and Eberhardt and Teal (2010)). In the case of a non-stationary variable, there is no extra useful information regarding the distribution (such as mean, and variance) could be obtain by simply adding more observations. What makes the situation worse is that the practice of time-averaging would not alter this property at all, which would cause serious effects on the estimation and inference (Granger and Siklos (1995); and Caselli (1996)). For example, in the time-series context, regressing a non-stationary variable on a set of non-stationary variables in a linear equation would cause ‘spurious regression’ problem if the estimated error term is not a stationary process. With this issue, the standard tests for significance and goodness of fit will be not suitable at all. Therefore, as the time span in dataset becomes longer, non-stationarity property should be taken into account prior to further empirical analysis.

Potential Issue 2: Slope Heterogeneity

It is not uncommon in existing growth empirics with short-panels to assume that the estimated coefficients are identical across countries/regions, which is normally referred as slope homogeneity assumption. Generally speaking, for studies that have used data at the global scale (e.g., Barro (2000), and Forbes (2000)), this restriction implies that each country with different level of economic development, such as Zimbabwe and United States of America, will have same parameters in growth regression.¹¹ However, this is a strong assumption, which is likely to be violated in reality. If slope parameters are in fact differed across each unit, fixed

¹¹ According to World Bank data, the GDP per capita in United States is about 46405 dollars, which is 100 times as much as the GDP per capita in Zimbabwe in 2014.

effect estimator, or first difference GMM estimator will generate inconsistent estimates for coefficients even when T becomes larger (Pesaran, *et al.*, 1996).

Potential Issue 3: CSD

Apart from slope homogeneity, another assumption in previous empirical research is cross-sectional independence. Phillips and Moon (1999) point out ‘...quite commonly in panel data theory, cross section independence is assumed in part because of the difficulties of characterizing and modelling across section dependence.’ However, the assumption that the covariance of the error terms is zero could be easily violated. Westerlund and Edgerton (2008) also support this point by saying ‘When studying macroeconomic and financial data..., cross-sectional dependencies are likely to be the rule rather than the exception, because of strong inter-economy linkages.’ Over recent years, panel data econometrics have witnessed an increasing research interest in characterizing and modelling CSD, and its impacts on estimation.

The impacts of CSD on estimation is determined by various factors such as the size of the correlation between individual (in our current research interest: province in China), and the nature of CSD itself. On the one hand, if CSD is induced by the unobserved common factors but it is not correlated to the dependent variables in the regression, FE estimator and RE estimator are still consistent, although they are inefficient and biased. On the other hand, the estimation through FE and RE estimators will be neither unbiased nor consistent if the covariances between interdependencies introduced by unobserved common shocks and regressors are not equal to zero. In the case of dynamic panel data econometrics, the effects of CSD on regression would be more complicated. But the consequence of neglecting CSD would be serious. Phillips and Sul (2003) put forward that pooling may decrease the efficiency dramatically over single equation OLS. In addition, ignoring CSD would lead to severely biased estimation especially for panel unit root tests and cointegration tests.

Preliminary Data Analysis

Prior to further empirical analysis, I firstly use the Pesaran's CSD test to detect the potential CSD. Pesaran (2004) formulates a test to detect systematic residual

correlation across different unit in the panel by employing pairwise correlation coefficients between regressors or residual series. The CSD test result followed by a standard FE estimation is reported in the table 3-1. It shows the existence of CSD as the result strongly rejects the null hypothesis of cross-sectional independence at 1% significance level.

Table 3-1. Results of FE Estimation and Pesaran's CSD Test

Variable	<u>FE Estimation</u>	
	Coefficient	p-value
Inequality	0.428	0.291
Investment	0.001	0.000***
Education	0.030	0.000***
<u>Pesaran's CSD test</u>		
CSD statistic	49.507	0.000***

Note: The FE estimation results are obtained from the regression $growth_{i,t} = \theta_{o,i} + \theta'_i x_{i,t} + \varepsilon_{i,t}$. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively. With respect to the Pesaran's CSD test, the null hypothesis is that the CSD is not present in the errors.

Then I test the time series properties of key variables with panel unit root tests, assuming homogeneous slopes and heterogeneous slopes, respectively. The test with former assumption is proposed by Levin, *et al.* (2002) (LLC). When allowing heterogeneous coefficients across province, I use the panel unit root test developed by Im *et al.* (2003) (IPS). In addition, in order to deal with the CSD, I also employ cross-sectionally augmented IPS (CIPS) suggested by Pesaran (2007), the test which allows for correlation between error terms across province to address the potential spurious inferences.

As reported in Table 3-2, individual trends and constants are included in the tests for inequality, investment, and education measure, while only deterministic time trends are excluded for economic growth in all panel unit root tests. Unlike other variables that normally exhibit a clear upward trend, economic growth is commonly not to be trending. LLC results in Table 3-2 show that the null hypothesis of unit root for all provinces could be firmly rejected at 1% significance level for both growth and education series, implying that these two series seem to follow $I(0)$ processes. Similarly, IPS test results also show that growth and education are $I(0)$ processes at 1% significance level. For the variables that are not stationary in its level form at 5% significance level, I further explore the time-series properties by

applying LLC and IPS panel unit root tests to their first difference values, which are shown in the bottom of the Table 3-3. For the first-differenced inequality and investment, only intercepts are included and all p-values imply that the null hypothesis should be rejected at 1% significance level, meaning that the level of inequality and investment are following $I(1)$ processes, in both LLC and IPS tests.

Table 3-2. LLC, IPS, and CIPS Panel Unit Root Test Results

	Deterministic Trend	LLC	IPS	CIPS
<u>A. Tests on its level form</u>				
Economic Growth	Intercept	0.000***	0.000***	-3.398***
Inequality	Trend, intercept	0.056*	0.987	-2.426
Investment	Trend, intercept	0.060*	0.999	-2.171
Education	Trend, intercept	0.000***	0.000***	-2.981***
<u>B. Tests on its first-difference form</u>				
Δ Inequality	Intercept	0.000***	0.000***	-4.291***
Δ Investment	Intercept	0.000***	0.000***	-3.509***

Note: I use Akaike Information Criterion to choose the optimal lag length by setting the maximum lag as 3. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Δ is an operator that calculate the difference between the value of variable at time t and t-1. In all the unit root tests, the null hypothesis is that the process is non-stationary.

3.4 Estimation Strategy

The next question in this chapter is how to examine the impacts of income inequality on economic growth in China. The empirical framework is the one based on a conditional convergence, which is derived from an extended version of the neoclassical Solow growth model (Barro, 1991, 1997, 2000). In the neoclassical model, the diminishing returns to the accumulation of physical and human capital imply that an economy's growth rate is depended on its initial level of development. In this sense, the previous literature that investigates the impacts of income inequality on economic growth use a reduced form regression, including economic growth as dependent variable, and measures of initial level of economic development, physical capital, human capital as independent variables. To address the issues of non-stationarity, slope heterogeneity, and CSD, I extend the traditional model with the ARDL, CS-ARDL, and CS-DL framework, allowing more dynamics of all variables. Under the context of growth empirics, I start with a standard panel ARDL (p_1, q_1, \dots, q_k) specification of the form

$$y_{i,t} = \sum_{\ell=1}^p \varphi_{i,\ell} y_{i,t-\ell} + \sum_{\ell=0}^q \beta'_{i,\ell} \mathbf{x}_{i,t-\ell} + \varepsilon_{i,t} \quad (3.2)$$

$$\varepsilon_{i,t} = \gamma'_i \mathbf{f}_t + u_{i,t} \quad (3.3)$$

Where the number of units $i = 1, 2, \dots, N$; the number of time periods $t = 1, 2, \dots, T$; $\mathbf{x}_{i,t-\ell}$ is a $k \times 1$ vector of regressors; $\beta_{i,\ell}$ are the $k \times 1$ coefficient vectors; $\varphi_{i,\ell}$ are scalars; \mathbf{f}_t is an $m \times 1$ vector of unobserved common factors; γ'_i is the corresponding factor loading. Model 3.2 can also be rewritten as the following Error Correction Model.

$$\Delta y_{i,t} = \lambda_i (y_{i,t-1} - \theta'_i \mathbf{x}_{i,t}) + \sum_{\ell=1}^{p-1} \varphi_{i,\ell}^* \Delta y_{i,t-\ell} + \sum_{\ell=0}^{q-1} \beta'_{i,\ell}^* \mathbf{x}_{i,t-\ell} + \varepsilon_{i,t} \quad (3.4)$$

Where $\lambda_i = -(1 - \sum_{\ell=1}^p \varphi_{i,\ell})$, which captures the speed of adjustment for any deviation from the long-run relationship; individual short-run coefficients are $\varphi_{i,\ell}^*$ and $\beta_{i,\ell}^*$; the ARDL relation can be calculated as $\varphi_{i,\ell}^* = \sum_{m=\ell+1}^p \varphi_{i,m}$ ($\ell = 1, 2, \dots, p-1$), and $\beta_{i,\ell}^* = -\sum_{m=\ell+1}^q \beta_{i,m}$ ($\ell = 1, 2, \dots, q-1$). The vector of long-run coefficients θ_i , which is of particular importance for investigating long-run relationships, is given by the equation 3.5. It is worth noting that θ_i can be consistently estimated regardless of whether the variables are $I(0)$ or $I(1)$, or whether the regressors are exogenous or endogenous (Pesaran & Shin, 1999).

$$\theta_i = \frac{\sum_{\ell=0}^q \beta_{i,\ell}}{1 - \sum_{\ell=1}^p \varphi_{i,\ell}} \quad (3.5)$$

One common way to estimate the long-run coefficients is to obtain the fitted value $\hat{\varphi}_{i,\ell}$ and $\hat{\beta}_{i,\ell}$ in the ARDL regression (equation 3.2), and then to plug the corresponding fitted values into equation 3.5 to compute θ_i . Alternatively, Chudik *et al.* (2013c) propose a new approach to estimate these long-run coefficients directly, which is referred as ‘distributed lag’ (DL) approach. They show that the equation 3.2 can be written as equation 3.6.

$$y_{i,t} = \theta_i x_{i,t} + \alpha'_i(L) \Delta \mathbf{x}_{i,t} + \tilde{\varepsilon}_{i,t} \quad (3.6)$$

Where $\tilde{\varepsilon}_{i,t} = \varphi(L)^{-1} \varepsilon_{i,t}$; $\varphi_i(L) = 1 - \sum_{\ell=1}^p \varphi_{i,\ell} L^\ell$; $\theta_i = \delta_i(1)$; $\delta_i(L) = \varphi_i^{-1}(L) \beta_i(L) = \sum_{\ell=0}^{\infty} \delta_{i,\ell} L^\ell$; $\beta_i(L) = \sum_{\ell=0}^q \beta_{i,\ell} L^\ell$; and $\alpha_i(L) = \sum_{\ell=0}^{\infty} \sum_{s=\ell+1}^{\infty} \delta_s L^\ell$. Chudik *et al.* (2013c) point out that there are several conditions that should be met in order to obtain a consistent estimate of θ_i . First, all the roots of $\varphi_i(L)$ should lie outside the unit circle. Second, the coefficients of $\alpha_i(L)$ are assumed to be exponentially decaying. Third, there is no reverse causality from lagged dependent variables to independent variables.¹² Similar to the ARDL approach, the strict exogeneity regarding the regressors is not a necessary assumption for the consistency of DL framework. Once the individual long-run coefficients $\hat{\theta}_i$ are estimated, either through ARDL or DL method, then these values are used to calculate the average long-run effects by averaging $\hat{\theta}_i$ across i , that is $\bar{\hat{\theta}}_{MG} = N^{-1} \sum_i^N \hat{\theta}_i$.

3.5 Main Empirical Results

Estimate Based on Panel ARDL Model

To explore the long-run impacts of income inequality of economic growth in China, I also include lags of both the dependent and the independent variables to capture the dynamics of the regression. Specifically, I initially employ the traditional ARDL model as baseline specification, which is shown in the following equation:

$$g_{i,t} = \theta_{0,i} + \sum_{\ell=1}^p \varphi_{i,\ell} g_{i,t-\ell} + \sum_{\ell=0}^p \beta'_{i,\ell} \mathbf{x}_{i,t-\ell} + \varepsilon_{i,t} \quad (3.7)$$

Where g corresponds to the growth rate of real GDP per capita; $\mathbf{x}_{i,t} = (theil_{i,t}, inevestment_{i,t}, education_{i,t})'$, the definition of these variables could be referred to the Table 3A-1 in appendix 3A, respectively; p corresponds to the lag length for each variable; $\theta_{0,i}$ is the unobserved province-specific and time-invariant factors. In model 3.7, the panel ARDL representation allows that parameters are

¹² If the feedback effects from the lagged values of left-hand-side variable to the regressors are present, the correlation between $\tilde{\varepsilon}_{i,t}$ and $\mathbf{x}_{i,t}$ will be non-zero, which invalidates the consistency of DL approach (Chudik, et al., 2013c).

different across each province, taking into account the fact that impacts of income inequality and other regressors on economic growth might vary for different provinces. In addition, through the panel unit root tests for all the variables of interest in our data, it can be concluded that economic growth and education measures are stationary process while investment and inequality index are following $I(1)$ process (as shown in Table 3-3). Regarding the lag length for independent or dependent variables, same lag orders p are applied to equation 3.7 but in different values, restricting the maximum lag length as 3. This practice has also been used in the empirical studies that have applied ARDL approach with similar sample size regarding T and N .¹³ Even though exactly specified lag lengths are necessary for the consistency of ARDL approach, Chudik *et al.* (2013c) argue that growth rates are moderately persistent so that the setting of up to 3 lags is enough to fully account for the short-run dynamics. Otherwise, using too much lags will lose much degrees of freedom in estimation, which would deteriorate the small sample performance.

The estimations of averaged long-run coefficients (across provinces) of inequality, investment, and education on economic growth, together with the mean estimate of the speed of adjustment from the panel ARDL model are reported for two cases, (a) and (b), in Table 3-3. Case (a) illustrates the estimation only includes inequality as regressor, while case (b) also contains investment and education measures. Panel A in Table 3-3 provides FE estimation which restrict the same parameters across provinces. By comparison, results obtained through MG estimator, which allows slope heterogeneity, are summarized in Panel B. For FE estimators and MG estimators, each panel provides the results across different lag lengths, namely, $p = 1, 2, \text{ and } 3$.

¹³ Chudik *et al.* (2013c) employ ARDL approach to estimate the long-run relationship between growth, debt, and inflation with at least 40 countries spanning from 1965 to 2010. Mohaddes and Raissi (2014) investigate the long-run relationship between growth and inflation by using the 14 state level data from 1989 to 2013 in an ARDL framework. In addition, under the ARDL framework, Huang and Yeh (2012) study the growth-inequality nexus in America across 48 states from 1945 to 2004. All of these empirical researches apply at most 3 lags in their specification or in their robustness checks.

Table 3-3. FE and MG Estimates Based on ARDL Approach

	ARDL (p=1)		ARDL (p=2)		ARDL (p=3)	
	(a)	(b)	(a)	(b)	(a)	(b)
<i>Panel A. FE Estimation</i>						
$\hat{\theta}_{theil}$	0.395 (0.551)	0.526* (0.314)	-0.208 (0.403)	0.096 (0.290)	-0.607 (0.629)	0.267 (0.418)
$\hat{\theta}_{invst}$		0.007*** (0.000)		0.0004* (0.0002)		0.0006* (0.0002)
$\hat{\theta}_{edc}$		0.012*** (0.004)		0.014*** (0.005)		0.008 (0.006)
$\hat{\lambda}$	-0.556*** (0.050)	-0.836*** (0.039)	-0.585*** (0.042)	-0.895*** (0.050)	-0.510*** (0.059)	-0.90*** (0.095)
CD test†	52.097***	45.215***	33.345***	22.724***	33.307***	18.460***
<i>Panel B. MG Estimation</i>						
$\hat{\theta}_{theil}$	-7.020 (4.412)	1.374 (8.974)	-1.965 (4.314)	39.072 (40.143)	-7.102* (4.081)	-6.417 (5.260)
$\hat{\theta}_{invst}$		-0.0005 (0.0006)		-0.003 (0.003)		-0.0003 (0.0008)
$\hat{\theta}_{edc}$		0.037** (0.017)		0.091* (0.053)		0.043 (0.027)
$\hat{\lambda}$	-0.686*** (0.041)	-1.038*** (0.052)	-0.718*** (0.045)	-1.197*** (0.069)	-0.742*** (0.078)	-1.762*** (0.116)
CD test†	44.61***	40.20***	26.72***	14.08***	22.01***	11.54***

Note. †CD test reports the CS statistics, instead of p-values. The panel ARDL specification is given by $g_{i,t} = \theta_{0,i} + \sum_{\ell=1}^p \varphi_{i,\ell} g_{i,t-\ell} + \sum_{\ell=0}^p \beta'_{i,\ell} \mathbf{x}_{i,t-\ell} + \varepsilon_{i,t}$. The reported standard errors in parenthesis are robust to cross-sectional heteroskedasticity and residual serial correlation. In particular, the standard errors are adjusted by clustering at the province level. ***, ** and * denote significance at 1%, 5%, and 10% levels, respectively.

The estimation results from Table 3-3 suggest that there is no long-run relationship between income inequality and economic growth in China. Across all the specifications, the long-run coefficients of inequality are not statistically significant (except for the coefficients in case (a) when $p = 1$, and in case (b) when $p = 3$ are only significant at 10% significance level). It cannot be predicted that there is positive or negative impact from inequality on growth because the signs of the coefficients are changing across different lag lengths. Under case (a) when only inequality and growth are considered, the results reveal the tendency that the effects of inequality are negative on economic growth. But the opposite result (even still insignificant) can be obtained when investment and education variables are included as shown in case (b) in both panels. Regarding the magnitude of the estimation results on inequality, the values ranging from -7.102 to 39.072 across various estimation techniques and lag orders. To be more specific, the absolute

value of coefficients on inequality are less than one by FE estimation while the larger absolute values are obtained by MG estimator.

Focusing on case (b) in both panels, it can be concluded that the long-run impact from investment and education on economic growth are positive. Specifically, different assumptions on parameters do not affect the absolute magnitude of investment coefficients as they are close to zero (ranging from -0.03 to 0.001). It is worth noting that the long-run coefficients of investment are negative and insignificant when I employ MG estimator, while its values are significantly positive based on FE estimators. For the long-run impacts of education, the results show that the coefficients on education are insignificant only in the case of $p = 3$, suggesting that once allowing for longer lags $p = 3$, the positive long-run effect of education on economic growth is no longer evident. Overall, the results presented in Table 3-3 imply inconclusive long-run inequality-growth nexus in China, and positive investment and education impact on long-run economic growth. However, the estimated results differ considerably with different lag lengths and assumption on slope homogeneity/heterogeneity. Another important result is that the CD-test statistics are so large that the null hypothesis of cross-sectional independence are strongly rejected at 1% in all cases.

Estimate Based on Panel CS-ARDL Model

The hypothesis of cross-sectional independent is strongly rejected at 1% level as shown in the bottom of Table 3-3, indicating that CSD should be a concern.

Ignoring the correlation between error terms across provinces would lead to misleading results (Phillips and Sul (2003)). To address the presence of CSD, I will use cross-sectionally augmented version of panel ARDL approach, proposed by Chudik *et al.* (2013c). These authors suggest to augment the original ARDL with cross-sectional averages of independent variables, the dependent variables, and a series of their lag values. In this chapter, I will follow the same practice as Chudik *et al.* (2013c), and Mohaddes and Raissi (2014) applied in a similar size of dataset regarding T and N by setting the lag length of averaged dependent and independent variables is 3 regardless of p . Technically, this panel CS-ARDL model can be specified as:

$$g_{i,t} = \theta_{0,i} + \sum_{\ell=1}^p \varphi_{i,\ell} g_{i,t-\ell} + \sum_{\ell=0}^p \beta'_{i,\ell} \mathbf{x}_{i,t-\ell} + \sum_{\ell=0}^3 \psi'_i \bar{\mathbf{z}}_{t-\ell} + \varepsilon_{i,t} \quad (3.8)$$

$$\bar{\mathbf{z}}_t = (\bar{g}_t, \bar{\mathbf{x}}'_t)' \quad (3.9)$$

Table 3-4 provides the MG estimation for CS-ARDL model. Case (a), which include only economic growth and income inequality, and case (b), which additionally includes investment and education measures, are estimated with mean group estimator for $p = 1, 2$, and 3. For the long-run coefficients on inequality, again, there is no evidence to support for the existence of growth-inequality nexus in the long term as these parameters are not statistically significant. When accounting for the effects of CSD, compared to the results from previous estimation, the range of $\hat{\theta}_{theil}$ even dramatically larger (falling between -77.103 to 63.763) and with indeterminate signs.

Apart from the insignificance of the income inequality coefficients, investment and education measures become insignificant as well, implying that when controlling for the CSD with the averaged lagged of dependent and independent variables, the long-run effects from both education and investment are no longer evident. What is even striking is that the sign of education, even though the coefficients are insignificant, are negative, suggesting that education would deteriorate the long-run economic growth. Compared to the previous results in Table 3-3, the magnitude of $\hat{\theta}_{invst}$ do not vary much, even though they are not statistically significant even at 10% level. It is worth noting that the total observation is not enough when considering the CS-ARDL model under $p = 3$, and when I try to implement the Pesaran' CD test in case (b) for all p values. These cases are marked as 'n.a.' in the table. As for the estimate of $\hat{\lambda}$, the speeds of convergence are generally faster compared to the case without CS augmentation in previous tests. The CD test statistics in Table 3-4 confirm a significant decrease in the average pair-wise correlation of error terms across provinces. However, it still cannot be rejected that the null hypothesis of cross-section independence.

Table 3-4. MG Estimates Based on the CS-ARDL Approach

	ARDL (p=1)		ARDL (p=2)		ARDL (p=3)	
	(a)	(b)	(a)	(b)	(a)	(b)
$\hat{\theta}_{theil}$	2.282 (7.631)	63.763 (50.061)	-1.459 (8.370)	2.092 (1.458)	-77.103* (80.532)	n.a.†
$\hat{\theta}_{invst}$		0.004 (0.010)		-0.013 (0.013)		n.a.
$\hat{\theta}_{edc}$		-14.91 (0.917)		-10.857 (10.168)		n.a.
$\hat{\lambda}$	-0.992*** (0.061)	-0.801*** (0.165)	-1.240*** (0.096)	-1.789*** (0.444)	-1.453*** (0.143)	n.a.
CD test†	-2.80***	n.a.	2.08**	n.a.	-1.87*	n.a.

Note. †CD test reports the CS statistics, instead of p-values.

‡n.a. stands for not applicable due to insufficient observation for relevant estimations when using certain lags to deal with potential serial correlation issues and CSD.

The panel CS-ARDL specification is given by $g_{i,t} = \theta_{0,i} + \sum_{\ell=1}^p \varphi_{i,\ell} g_{i,t-\ell} + \sum_{\ell=0}^p \beta'_{i,\ell} \mathbf{x}_{i,t-\ell} + \sum_{\ell=0}^3 \psi'_{i,\ell} \bar{\mathbf{z}}_{t-\ell} + \varepsilon_{i,t}$. Standard errors are reported inside parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Estimate Based on Panel CS-DL Model

Even though the CS-ARDL approach have tackled the issue of cross-sectional dependence caused by common factors, Chudik *et al.* (2013c) point out that both ARDL and CS-ARDL approaches are not without its disadvantages. Based on their Monte Carlo simulation results, these authors conclude that the sampling uncertainty for ARDL and CS-ARDL model could be large especially for the case that the time periods is moderate. In addition, another drawback of ARDL model is that the slight misspecification of the model regarding the lag length would deteriorate the estimation performance severely. Therefore, Chudik *et al.* (2013c) propose a new approach to estimate the long-run coefficients, θ_i directly without estimating the short-run dynamics, which is referred as DL approach as introduced in equation 3.6 previously. The DL approach features better small sample performance for moderate T . Furthermore, the DL model only requires that a truncation lag order is selected since it is robust to residual serial correlation, and possible breaks in the error terms, which are appealing features in empirical research.

In order to account for the effect of CSD, CS-DL approach augments the equation 3.6 with the averaged lag values of independent variables, and the averaged value of first-differenced dependent variable. However, at the same time, this new

method drops out the autoregressive term in the right-hand-side. In the following context, I will use the MG estimator to run the CS-DL regressions in case (a) (includes only income inequality and economic growth), and case (b) (also includes investment and education). Similarly, different lag lengths are considered for $p = 1, 2, 3$ whereas I set a fixed lag order of 3 for averaged values for regressors in all specifications.

$$g_{i,t} = \theta_{0,i} + \boldsymbol{\theta}'_i \mathbf{x}_{i,t} + \sum_{\ell=0}^{p-1} \delta'_{i,\ell} \Delta \mathbf{x}_{i,t-\ell} + \omega_{i,g} \Delta \bar{g}_t + \sum_{\ell=0}^3 \omega'_{i,x\ell} \bar{\mathbf{x}}_{t-\ell} + \varepsilon_{i,t} \quad (3.10)$$

Table 3-5 summarizes the MG estimation based on CS-DL framework. It is worth noting that this estimation is not applicable for the case (b) when $p = 2$ and $p = 3$ since there is not enough observations in the panel. Overall, in all specification, the long-run coefficients on income inequality, are still statistically insignificant even at 10% level, even though all of them are positive, suggesting that the long-run impact of income inequality on growth is encouraging. Focusing on the only estimable specification of case (b), the magnitude of the long-run coefficient of inequality are unusually high (reaching 22.410). Meanwhile, the coefficients on investment (insignificant) and education (significant at only 10% level) measure are negative, which is similar to the results obtained by CS-ARDL (see Table 3-4). At the bottom of the Table 3-5, the Pesaran's CD test statistics suggest that the CSD caused by common factors have not completely ruled out by augmenting the regression with average term of related variables.

Table 3-5. MG Estimates Based on the CS-DL Approach

	DL (p=1)		DL (p=2)		DL (p=3)	
	(a)	(b)	(a)	(b)	(a)	(b)
$\hat{\theta}_{theil}$	-6.723 (4.826)	22.410 (15.193)	7.699 (4.965)	n.a.	6.282* (5.251)	n.a.†
$\hat{\theta}_{invst}$		-0.003 (0.002)		n.a.		n.a.
$\hat{\theta}_{edc}$		-0.353* (0.208)		n.a.		n.a.
CD test†	-3.10***	-0.83	2.96***	n.a.	-2.64***	n.a.

Note. †CD test reports the CS statistics, instead of p-values.

‡n.a. stands for not applicable due to insufficient observation for relevant estimations when using certain lags to deal with potential serial correlation issues and CSD.

The panel CS-DL specification is given by $g_{i,t} = \theta_{0,i} + \theta'_{i,t} \mathbf{x}_{i,t} + \sum_{\ell=0}^{p-1} \delta'_{i,\ell} \Delta \mathbf{x}_{i,t-\ell} + \omega_{i,g} \Delta \bar{g}_t + \sum_{\ell=0}^3 \omega'_{i,x\ell} \bar{\mathbf{x}}_{t-\ell} + \varepsilon_{i,t}$. Standard errors are reported inside parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

As Chudik *et al.* (2013c) discussed, however, the consistency of the CS-DL estimation requires that there is no reversed effect running from the lagged of the dependent to the regressors, which has been proved by their Monte Carlo simulation. Practically, to ensure the CS-DL method is valid, one should assume that the economic growth rates in previous period do not affect the current or previous investment ratio, or education enrolment. Having said that, Chudik *et al.* (2013c) emphasize that the CS-DL approach itself is not a superior model compared to CS-ARDL model because both technique involve a trade-off. For example, it is easier to calculate the long-run relationship by collecting the short-run coefficients in ARDL framework. But the bad small sample performance and correct model specification regarding lag length are disadvantages. While DL model offer better small sample performance and robust results to different lag order, it leaves the feedback effects problem unsolved.

3.6 Robustness Analysis

OLS Estimation for Each Period

In the first part of this section, simple OLS estimation will be employed for each period to test the relationship between income inequality and economic growth with the following specification:

$$g_i = \theta_0 + \theta_1 Theil_{i,-1} + \theta_2 Investment_{i,-1} + \theta_3 Education_{i,-1} + \varepsilon \quad (3.11)$$

Where i denotes province while subscript -1 means the value in the last period for this variable. For example, when testing the model 3.11 for year 1988, economic growth rate, as the dependent variable, will choose its value in 1988. But for other independent variables, their values in 1987 will be selected in this case. This model specification is following previous empirical research such as Persson and Tabellini (1994), Li and Zou (1988), Forbes (2000), and Panizza (2002). This practice not only rules out the possible reverse causality from the current economic growth to the regressors in the current realization (Persson & Tabellini, 1994), but also takes the lag effect into account since it is common that the current change in education or investment will not have immediate effect on the economic growth. Table 3-6 shows the results of OLS estimation for model 3.11 from 1988 to 2012. The results reveal that the coefficients for the lagged valued of Theil index are not statistically significant at 5% confidence level (three exceptions happened in 1991, 2008 and 2011). Similar results could also be obtained regarding lagged investment and education, which violates the general believe and previous empirical evidence. With respect to lagged value of education measures, none of the coefficient is significant at 5% level. It can be concluded that from the simple OLS estimation for model 3.11, the correlation of current inequality, investment, and education do not have significant relationship with the subsequent economic growth.

Table 3-6. OLS Result for Each Period

Year	L.Theil	L.Investment	L.Education	Constant	N
1988	0.557	0.001	-0.005	0.014	28
1989	-0.108	0.001	-0.029	0.062	29
1990	1.978	-0.002	-0.053	0.127**	29
1991	3.669*	-0.001	-0.067	0.110*	29
1992	2.196	0.001	-0.078	0.089	29
1993	-0.043	0.001	-0.056	0.068	29
1994	0.825	-0.001	-0.012	0.081*	29
1995	1.271	-0.003*	0.023	0.142**	29
1996	0.024	-0.002	0.012	0.124**	29
1997	0.410	-0.001	0.031	0.084***	29
1998	0.287	-0.000	0.017	0.077***	29
1999	-0.029	-0.000	0.022	0.068***	29
2000	-0.877	0.001	0.026	0.059*	29
2001	0.158	-0.000	0.002	0.086***	29
2002	0.481	-0.000	0.008	0.106***	29
2003	0.281	0.001	0.002	0.100***	29
2004	-0.339	0.001	0.011	0.104**	29
2005	-0.885	0.001	0.004	0.107**	29
2006	-0.438	0.001	-0.001	0.098***	29
2007	0.191	0.001*	-0.005	0.070*	29
2008	-2.291*	0.003*	0.019	-0.029	29
2009	-0.577	0.001	0.010	0.009	29
2010	-1.033	0.000	-0.004	0.097*	29
2011	-0.847*	0.001***	-0.010	0.063**	29
2012	-0.279	0.001**	-0.003	0.006	29

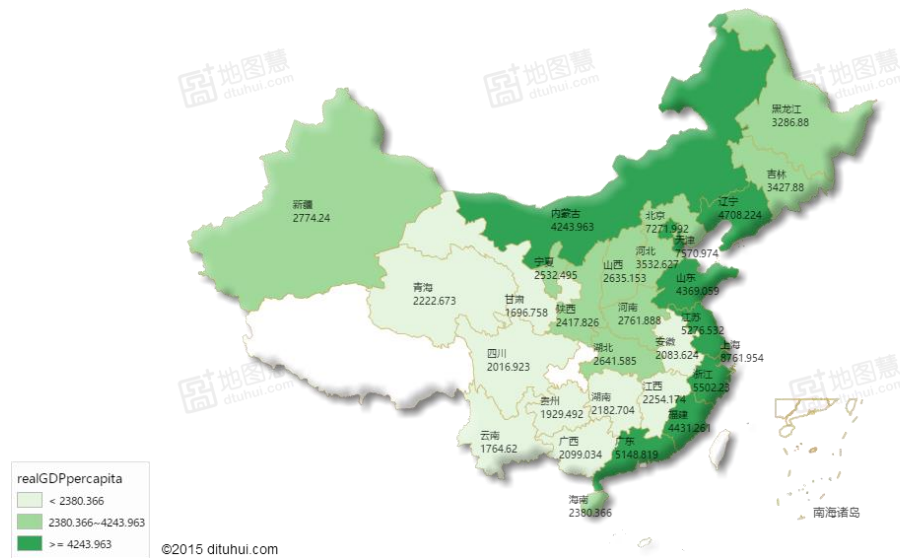
Note. ***, **, and * denote significance at the 1%, 5%, and 10% levels. The OLS specification is given by $g_i = \theta_0 + \theta_1 Theil_{i,-1} + \theta_2 Investment_{i,-1} + \theta_3 Education_{i,-1} + \varepsilon$

Analysis with Subsamples

From previous estimation via ARDL, CS-ARDL or CS-DL model, it can be concluded that the long-run relationship between income inequality and economic growth in China is not significant since the long-run coefficients on Theil index are statistically insignificant at 10% significance level for most of the cases. With the worldwide dataset, Barro (2000) concludes that the relationship between inequality and economic growth is non-linear: he finds that there is positive growth-inequality nexus in rich countries whereas the correlation between inequality and growth is negative among poor countries. However, when the whole sample is considered, the overall relationship between income inequality and growth rates are not evident. In addition, such non-linear inequality-growth nexus is also obtained in Reuter (2004) and Wan *et al.* (2006). Therefore, following these thoughts, it is reasonable to

assume that the impacts of income inequality on economic growth might vary in provinces with different economic performance. To verify this assumption, I categorize the whole sample into three subsamples, namely, top10, middle10 and bottom9.

Figure 3-1. Economic Development of top10, middle10 and bottom9 Provinces



Source: Author's own calculation from NBS

First, all provinces are ranked from the highest to the lowest by the averaged real GDP per capita from 1987 to 2012. In this sense, the richest 10 provinces fall in the group of top10 while the 9 provinces with the lowest averaged GDP per capita will be grouped as bottom9. The remaining provinces belong to the middle10 classification. The result reveals that the overall averaged real GDP per capita is 3562 renminbi (approximately 350 GBP based on the current exchange rate in 2015) during 1987 to 2012, with the highest at 8762 renminbi (Shanghai) and the lowest at 1292 renminbi (Guizhou). The real GDP per capita for the top 10 provinces are equal to or above 4244 renminbi whereas its value for the bottom 9 provinces is equal to or under 2254 renminbi. Table 3-7 summarized the whole ranking and related descriptive statistics regarding real GDP per capita for every province. Also, Figure 3-1 shows the distribution of top10, middle10 and bottom9 provinces in a Chinese map.

Table 3-7. Real GDP Per Capita and Ranking for Provinces in China

Top10			Middle10			Bottom9		
Rank	Province	GDP	Rank	Province	GDP	Rank	Province	GDP
1	Shanghai	8762	11	Hebei	3533	21	Jiangxi	2254
2	Tianjin	7571	12	Jilin	3428	22	Qinghai	2223
3	Beijing	7272	13	Heilongjiang	3287	23	Hunan	2183
4	Zhejiang	5502	14	Xinjiang	2774	24	Guangxi	2099
5	Jiangsu	5277	15	Henan	2762	25	Anhui	2084
6	Guangdong	5149	16	Hubei	2642	26	Sichuan	2017
7	Liaoning	4708	17	Shanxi	2635	27	Yunnan	1765
8	Fujian	4431	18	Ningxia	2532	28	Gansu	1697
9	Shandong	4369	19	Shaanxi	2418	29	Guizhou	1292
10	Neimenggu	4244	20	Hainan	2380			
Mean		3562	Medium			2762		

Source: Author's own calculation from NBS.

As shown in the Figure 3-1 and Table 3-7, the top 10 richest provinces are normally distributed around the east coastal line (except for Neimenggu), while the poorest provinces are in the western part of China (except for Xinjiang). Also, the middle 10 provinces are laying between the eastern richest and the western poorest in the map. In the following subsection, this study will provide the estimation results via the estimators and models that have been used in whole sample: dynamic FE and MG estimators for ARDL model, CS-ARDL model, and CS-DL model, respectively.

Estimation Results for Top10

Table 3-8 summarizes the estimation results obtained from ARDL, CS-ARDL and CS-DL model. FE estimation results for the richest 10 provinces show that the long-run coefficient on all regressors are insignificant even at 10% confidence level when $p = 2$. In the case of ARDL(1) and ARDL(3) specification, the results reveal that coefficients on Theil index are mostly positive and significant (4 out of 6 cases) at least at 10% confidence level, ranging from 0.449 to 1.218. With regard to other variables, the results show that there is no long-run relationship between education and economic growth, while investment has been proved to exert encouraging effects on growth. However, similar results could not be further confirmed by using MG for the identical specifications. Specifically, the long-run coefficients on Theil index are not significant in all cases when considering the MG estimator on ARDL model. Interestingly, the results in panel B obtained via MG estimator show that investment has nothing to do with economic growth due to insignificant parameters,

while it can be concluded that education has negative effects on economic growth for the richest 10 provinces. Both results violate from traditional theories and empirical results.

Since the number of cross-sections are at most 10 for each subsample ($N = 10$), there is not enough observation to calculate the related coefficients via CS-ARDL and CS-DL model. Therefore, in the similar analysis to Middle10 and Bottom9 provinces, I cannot provide analysis when considering the case of four variables in CS-ARDL(2) and CS-ARDL(3) specifications. For CS-ARDL results, only one coefficient of interest (Theil index) is significant at 10% confidence level, implying that the long-run relationship between inequality and growth is positive. However, compared to the parameters obtained from model without cross-sectional augment, the magnitude of this coefficient (7.01) is significantly larger than the ones obtained via fixed effects (maximum 1.22). With respect to CS-DL model, it can be concluded that there is no long-run inequality-growth nexus, but both investment and education are negatively affect the economic growth, which violate our expectation as well.

Table 3-8. Estimation Results for Top10 Subsample

	ARDL (p=1)		ARDL (p=2)		ARDL (p=3)	
	(a)	(b)	(a)	(b)	(a)	(b)
<i>Panel A. FE for ARDL</i>						
$\hat{\theta}_{theil}$	10.30***	1.22**	-0.11	0.47	-0.45*	0.87***
$\hat{\theta}_{invst}$		0.001***		0.0004		0.0005*
$\hat{\theta}_{edc}$		0.00		0.001		0.000
$\hat{\lambda}$	-0.48***	-0.70***	-0.59***	-0.83***	-0.54***	0.084***
<i>Panel B. MG for ARDL</i>						
$\hat{\theta}_{theil}$	1.81	1.51	-1.66	0.081	-4.97	-3.63
$\hat{\theta}_{invst}$		0.00		-0.002*		-0.0002
$\hat{\theta}_{edc}$		-0.01		0.06*		0.06*
$\hat{\lambda}$	-0.59***	-0.87***	-0.65***	-1.10***	-0.62***	-1.68***
<i>Panel C. MG for CS-ARDL</i>						
$\hat{\theta}_{theil}$	-0.91	7.01*	0.26	n.a.	-0.16	n.a.
$\hat{\theta}_{invst}$		0.20		n.a.		n.a.
$\hat{\theta}_{edc}$		-0.25		n.a.		n.a.
$\hat{\lambda}$	-1.02***	-1.41***	-1.41***	n.a.	-1.45***	n.a.
	DL (p=1)		DL (p=2)		DL (p=3)	
	(a)	(b)	(a)	(b)	(a)	(b)
<i>Panel D. MG for CS-DL</i>						
$\hat{\theta}_{theil}$	-0.19	11.86*	0.44	n.a.	0.86	n.a.
$\hat{\theta}_{invst}$		-0.006**		n.a.		n.a.
$\hat{\theta}_{edc}$		-0.41***		n.a.		n.a.

Note. n.a. stands for not applicable due to insufficient observations for relevant estimation while using certain lags to deal with potential serial correlation issue and CSD. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Estimation Results for Middle10

The estimation results from middle 10 provinces, as shown in Table 3-9, reveal a different story compared to those in Top10. Specifically, focusing on FE estimator, the long-run coefficient on Theil index turn to be negative and significant in most of cases (except for ARDL(2) case (b), and ARDL(3) case (b)), implying that income inequality will impede the economic growth in the long-run, ranging from -9.03 to -4.21. This result also can be confirmed by the MG estimator, even though the range of the significant coefficients are marginally larger than those obtained by FE estimator (from -13.01 to -9.66). Also, even though FE estimation do not provide clear evidence regarding the impact of investment on economic growth, all education long-run coefficients are positive and significant at least at 5% significance level. This evidence also is strengthened by the MG estimator for the same specifications. Except for the ARDL(1), the case that reveal that education is

negatively associated to economic growth, all of other cases show that education is one of economic growth stimulators.

With regard to the cases when cross-sectional dependence is taken into consideration, overall coefficients on Theil index are much larger than those of previous estimation. However, there is only one case to show that inequality-growth nexus is positive (at 10% confidence level), which is also opposite to the prediction of what have been concluded by ARDL model. As for other regressors, none of them are statistically significant in all cases in CS-ARDL specifications.

Table 3-9. Estimation Results for Middle10 Subsample

	ARDL (p=1)		ARDL (p=2)		ARDL (p=3)	
	(a)	(b)	(a)	(b)	(a)	(b)
<i>Panel A. FE for ARDL</i>						
$\hat{\theta}_{theil}$	-9.03***	-4.53***	-4.21**	0.61	-7.23*	-1.782
$\hat{\theta}_{invst}$		0.0003		-0.001		0.001
$\hat{\theta}_{edc}$		0.002**		0.047***		0.036**
$\hat{\lambda}$	-0.64***	-0.90***	-0.66***	-0.93***	-0.66***	-1.01***
<i>Panel B. MG for ARDL</i>						
$\hat{\theta}_{theil}$	-11.62***	12.32	-9.77	109.6	-9.66	-13.01*
$\hat{\theta}_{invst}$		-0.001		-0.011		-0.001*
$\hat{\theta}_{edc}$		-0.048**		0.227*		0.076***
$\hat{\lambda}$	-0.68***	-1.07***	-0.75***	-1.09***	-0.88***	-1.85***
<i>Panel C. MG for CS-ARDL</i>						
$\hat{\theta}_{theil}$	9.46	1.36	10.93	n.a.	10.71*	n.a.
$\hat{\theta}_{invst}$		0.015		n.a.		n.a.
$\hat{\theta}_{edc}$		-0.394		n.a.		n.a.
$\hat{\lambda}$	-1.04***	-1.54***	-1.22***	n.a.	-1.43***	n.a.
	DL (p=1)		DL (p=2)		DL (p=3)	
	(a)	(b)	(a)	(b)	(a)	(b)
<i>Panel D. MG for CS-DL</i>						
$\hat{\theta}_{theil}$	12.99	76.76	14.54	n.a.	17.48	n.a.
$\hat{\theta}_{invst}$		-0.003**		n.a.		n.a.
$\hat{\theta}_{edc}$		-0.587***		n.a.		n.a.

Note. n.a. stands for not applicable due to insufficient observations for relevant estimation while using certain lags to deal with potential serial correlation issue and CSD. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Estimation Results for Bottom9

Table 3-10 summarizes the estimation results for the poorest 9 provinces. Through the tests (FE estimator and MG estimator) for ARDL model, the long-run coefficients, $\hat{\theta}_{theil}$, are insignificant in most of the cases (8 out of 12). Focusing on the significant results, it can be concluded that the income inequality is negatively

associated to the long-run economic growth at least at the 10% significance level, ranging from -11.67 to -3.328. Also, the significant long-run coefficients on Theil index for the poorest 10 provinces share the similar magnitude to the ones in the Middle10 subsample. With regard to other variables, results through FE estimator show that there is no long-run relationship between investment and growth, and between education and growth, as all the parameters of interests are not significant at 5% significance level. When MG estimator is considered for ARDL specification, it can be concluded that education exerts positive impacts on economic growth in the long-run. Such positive education-growth nexus also is supported by the results from CS-ARDL and CS-DL specification. However, when considering the CSD, the size of the coefficients changes dramatically. For example, on the one hand, in the case of CS-ARDL(1), the coefficient of education is about 10 times as much as the one obtained from ARDL(1). On the other hand, in the case of CS-DL(1) specification, the corresponding coefficient on education is 0.0039, which is only less than one-tenth as much as the one obtained from ARDL(1). With respect to other variables such as inequality and investment, results from CS-ARDL and CS-DL do not reveal clear inequality-growth nexus and investment-growth nexus evidence as the related coefficients are insignificant at 5% level.

Table 3-10. Estimation Results for Bottom9 Subsample

	ARDL (p=1)		ARDL (p=2)		ARDL (p=3)	
	(a)	(b)	(a)	(b)	(a)	(b)
<i>Panel A. FE for ARDL</i>						
$\hat{\theta}_{theil}$	-9.98**	-3.11	-2.51	0.61	-11.67**	-3.328*
$\hat{\theta}_{invst}$		0.001		-0.001		0.001*
$\hat{\theta}_{edc}$		0.02		0.047***		0.002
$\hat{\lambda}$	-0.62***	-0.95***	-0.56***	-0.93***	-0.42***	-0.80***
<i>Panel B. MG for ARDL</i>						
$\hat{\theta}_{theil}$	-11.72***	-10.94*	6.37	109.6	-6.74	-2.19*
$\hat{\theta}_{invst}$		-0.001		-0.011		-0.002
$\hat{\theta}_{edc}$		0.08*		0.227*		0.122**
$\hat{\lambda}$	-0.80***	-1.20***	-0.75***	-1.09***	-0.73***	-1.76***
<i>Panel C. MG for CS-ARDL</i>						
$\hat{\theta}_{theil}$	14.93	19.24	14.48	n.a.	-5.23	n.a.
$\hat{\theta}_{invst}$		0.008		n.a.		n.a.
$\hat{\theta}_{edc}$		0.83*		n.a.		n.a.
$\hat{\lambda}$	-1.21***	-1.54***	-1.58***	n.a.	-1.97***	n.a.
	DL (p=1)		DL (p=2)		DL (p=3)	
	(a)	(b)	(a)	(b)	(a)	(b)
<i>Panel D. MG for CS-DL</i>						
$\hat{\theta}_{theil}$	13.26*	-12.74	14.83**	n.a.	12.86	n.a.
$\hat{\theta}_{invst}$		-0.004*		n.a.		n.a.
$\hat{\theta}_{edc}$		-0.357***		n.a.		n.a.

Note. n.a. stands for not applicable due to insufficient observations for relevant estimation while using certain lags to deal with potential serial correlation issue and CSD. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Concluding Remarks

This study divides the full sample in three subsamples according to the averaged real GDP per capita during 1987 to 2012 for each province. To examine the subsamples, similar techniques (FE and MG estimators for ARDL, MG estimator for CS-ARDL and CS-DL model) to the ones that have been employed to the full sample are used to three subsamples. Due to insufficient panel observations, the estimation on CS-ARDL and CS-DL model with $p = 2$ and $p = 3$ via MG estimator cannot be conducted. Therefore, there are 'n.a.' in the corresponding areas in Table 3-8, Table 3-9, and Table 3-10. In addition, the coefficients obtained through CS-ARDL and CS-DL specification are more likely larger and insignificant compared to those from ARDL specifications. For this reason, the subsample analysis only focuses on FE and MG estimators for ARDL specification allowing up to 3 lags.

Overall, the estimation results for subsamples imply that there is a relatively weak positive relationship between income inequality and economic growth in the long-run for the richest 10 provinces, whereas the impacts of income inequality on economic growth for the rest of provinces are negative during the same observed time periods. In comparison, when considering the same model specification and estimators for the whole sample, the results imply that the long-run correlation between income inequality and economic growth in China is not evident. Therefore, it can be concluded that the relationship between inequality and growth is non-linear, which supports the findings in Barro (2000). Focusing on the size of the coefficients on Theil index among the subsamples, the absolute values of $\hat{\theta}_{theil}$ are much smaller in Top10 than their counterpart provinces (Bottom9 and Middle10), indicating that the impacts of inequality in rich areas are weaker than that of in the poor and medium provinces. However, the statistical significance of the long-run coefficients of Theil index are not robust across different lags. It is shown in Table 3-8, Table 3-9, and Table 3-10 that the number of insignificant $\hat{\theta}_{theil}$ almost accounts for half of the total cases in each subsample.

Similar to the long-run coefficients on Theil index, the coefficients on other variables are not persistently significant across models in different lag lengths. Surprisingly, the estimation results do not show that investment exert any significant impact on long-run economic growth for Middle10 and Bottom9, as majority of the coefficients on investment are insignificant, which is different from the expectation that investment is one of the promoters of economic growth. In comparison, in the case of the Top10 rich provinces, only half of the coefficients on investment are positively significant, suggesting that investment encourages the long-run growth rate. However, the effects of investment on growth, no matter for Top10 or for the whole sample, are marginal. With regard to education, the related results from Middle10 and Bottom9 consistently deliver the message that education is positively correlated to the economic growth in the long-run. However, the results from rich provinces show an opposite story that education is negatively linked to the long-run growth, even though the majority of long-run coefficients on education in Top10 are not significant.

In conclusion, when splitting the whole sample into subsamples by the real GDP per capita in each province, the results show that there is a positive inequality-growth nexus among richest 10 provinces while its relationship is negative for the rest of China. In addition, investment is not significant in the most of cases, even for cases in subsamples. Furthermore, similar to the results from whole sample, education in middle 10 and poorest 9 provinces exerts positive impacts on long-run economic growth. However, this relationship is not evident among the richest 10 provinces.

3.7 Conclusion and Discussion

The impacts of income inequality of economic growth have long been a core research interest among economists for the past decades, which is the very first research question of this thesis. Especially, China is an interesting case because it has been witnessed a remarkable economic growth accompanied by a dramatic increase in the level of income inequality since the commencement of the economic reform from 1978. Empirically, this chapter identifies the long-run impacts of income inequality on economic growth.

The current research aims at overcoming some data deficiencies in existing empirical research in Reuter (2004), Wan *et al.* (2006), and Gravier-Rymaszewska *et al.* (2010) by employing the new dataset assembled by UTIP. Also, with a larger panel in both cross-section units and time span, new panel time series estimation techniques, taking non-stationarity, parameter heterogeneity, and CSD into consideration. These methods include FE and MG estimators for ARDL, CS-ARDL, and CS-DL model.

The empirical results show that there is no significant correlation between income inequality and economic growth in China when the tests are conducted for the whole sample as the estimation results are consistently insignificant. However, when the whole sample is categorized by the economic performance, the results become different. The long-run coefficients on Theil index for the richest 10 provinces are positive while those are negative for the Middle10 and Bottom9 areas. This finding is similar to what have been concluded in Barro (2000), the study which points out a non-linear relationship that the inequality-growth nexus is

positive for rich countries while the impact of inequality on growth is negative for poor countries. But the estimation results regarding the long-run effect coefficients of the income inequality are not persistently significant across different lag lengths for each subsample.

Compared to the findings in previous empirical research in China, the results are similar to Gravier-Rymaszewska *et al.* (2010), the study which finds out that the impact of inequality on industrial growth is positive in coastal areas. However, different Theil index employed in both research is not the only different in both research. Therefore, anything different or similar of the result between these two studies cannot be explained by the improved of the dataset only.

One important policy implication of current research is that the inequality-reduction-policy should be considered in a region-by-region case as the impacts of inequality have different effects on rich and the rest of the provinces in China. For the poor areas, since the inequality-growth nexus is negative, meaning that the policies that could lower the level of inequality would encourage the economic growth. However, one should be concerned that the same policies might not be applied to the rich provinces unless that the prior goal of the government to reduce the inequality at the expense of high growth rate.

There are several aspects can be done in the future to improve current research. First of all, even though the data that this chapter have the largest coverage at the best of my knowledge in the Chinese context, the dataset itself has still not enough observations. The results are shown in the empirical results section contain some 'n.a.' as there is not enough panel observation to calculate the needed coefficients. For this reason, if longer time periods can be covered, the time-series properties can be more clearly tested, and more lags can be selected with ARDL, CS-ARDL, and CS-DL model, to better tackle with the CSD issue. Second, even though the cross-sectional dependence has been taken into account in this chapter, with limit data and limit lags that can be exploited in the cross-sectionally augmented terms, the CSD problem still cannot be ruled out completely. In future work, researchers can figure out a better way to model this CSD or another way to mitigate the impacts of these dependencies.

So far, this chapter has examined the long-run effect of income inequality on economic growth in China with the macro economic data at the province level. But what can we tell the impact of income inequality at the micro level? It will be interesting to look at this issue from the household/individual perspective. In the next chapter, I will provide the related empirical evidence from the micro level as well.

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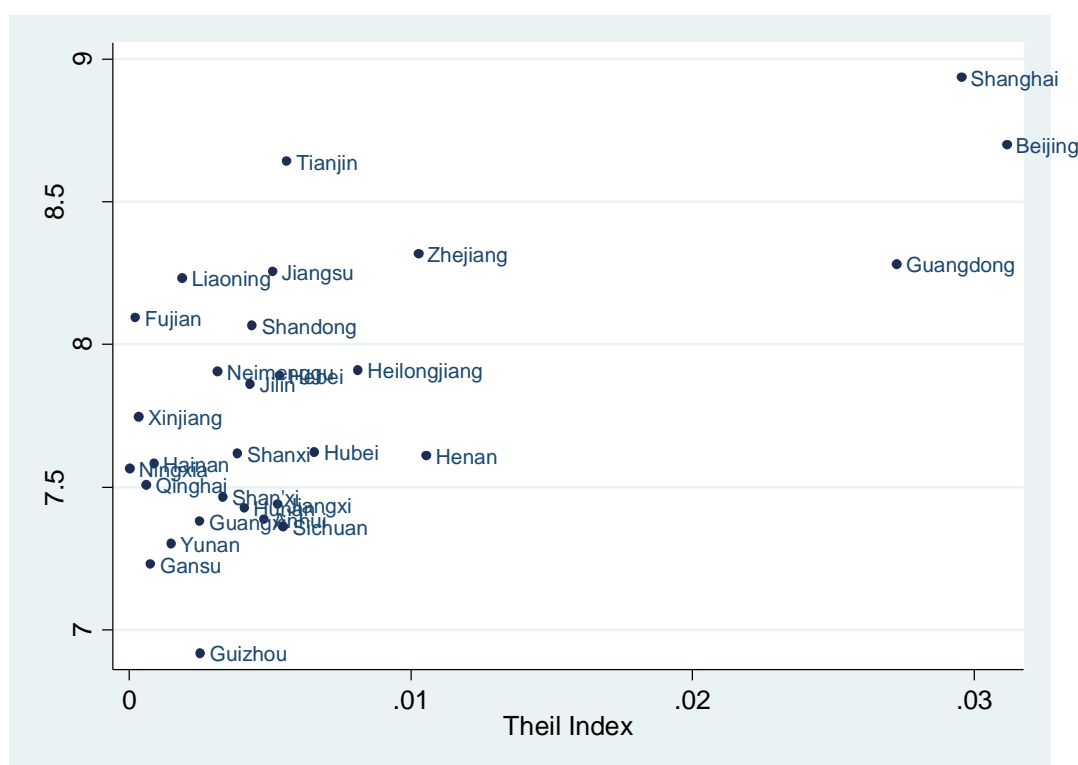
Appendix 3A Information Regarding the Variables

Table 3A-1. Descriptive Statistics of Key Variables

Variable	Definition	Source	Mean	S.D.
Growth	$\Delta \log(\text{real GDP per capita})^*$	NBSC	0.0872	0.056
Inequality	Theil Index	UTIP	0.001	0.011
Investment (%)	Fixed capital/Investment and GDP	NBSC	41.207	16.603
Education (%)	Higher Education Enrolment Rate	NBSC	0.797	0.748

Note: Δ is an operator that calculates the difference between the value of variable at time t and $t-1$.

Figure 3A-1. Scatter Plot (Growth vs. Theil)



Data Source: Author's computation based on the raw data from NBSC and UTIP.

Note: Shanghai, Tianjin, Beijing, Zhejiang, Jiangsu and Guangdong are the richest provinces (as can be seen in Table 3-7, while the poorest 5 provinces are Guizhou, Gansu, Yunnan, Sichuan, and Anhui, which are located in the right-bottom of the scatter plot.

Chapter 4. Effects of Inequality on Growth: Aggravation from Aggregation?

4.1 Introduction

The impacts of income inequality on economic growth has long been one of core research interests among economists, politicians, or sociologists. Although the related studies on this line remains controversial, the notion of a trade-off between equity and efficiency seems deeply rooted in policymakers' consciousness, which is originally proposed in Okun (1975). From a perspective of policy makers, it seems that, to some extent, the goal of preventing income inequality from increasing and the goal of maintaining a sustainable economic growth are contradictory. Is it really the case? Related literature has been motivated to investigate the inequality-growth nexus. Interestingly, so far, the effects of income inequality on economic growth is still inconclusive. In terms of empirical studies, majority of them run a standard growth regression with a measure of income inequality as an extra explanatory variable with global data (see Alesina and Rodrik, 1994; Persson and Tabellini, 1994; and Clarke, 1995; Forbes, 2000; Barro, 2000). With different estimation techniques and various models, both positive and negative coefficients on income inequality are found.¹

There are several drawbacks to the majority of the existing empirical literature in this area. Most of research focuses on global data, ignoring potential heterogeneity across countries/economies. Given the variation results across countries, policy makers need to ask whether particular conclusions may be applied to their countries. This question is especially critical after Barro's (2000, 2008) finding that income inequality has different effects on economic growth between poor and rich countries. These studies offer great examples to illustrate that failure in considering the degree of development will lead to a misleading general conclusion for all countries.

¹ Initially, Alesina and Rodrik (1994), Persson and Tabellini (1994), and Clarke (1995) conclude that the impacts of inequality on economic growth is negative. However, with introduction of the improved dataset and panel data estimation techniques, Forbes (2000) and Barro (2000) challenge the previous empirical evidence and find a positive inequality-growth relationship.

The second drawback relates to macro data (or aggregate data) that have been widely used to investigate the impacts of income inequality on economic growth. There are at least two potential issues that will affect the estimation result. The first is that the previous literature pays little attention to the curvature of the growth function at the micro level. When testing whether economic convergence occurs across countries, traditional growth empirics normally assume that the economic growth is linearly correlated with the initial income level, ignoring the possibilities of curvature (such as quadratic or inverse correlation) at the micro level. This chapter finds that different curvatures of the income growth function at the micro level will have different impacts on the marginal effect of income inequality on aggregate income growth. Specifically, if a quadratic term of initial income level is introduced to the micro growth function, then the association between income inequality and macro income growth will not necessarily to be negative. A mathematical example is offered to illustrate this issue in the next section. Another potential concern is the aggregating variables to produce macro data. Ideally, the macro data should be the algebraic mean of the micro index. However, aggregation effect will be raised in the macro growth empirics. For example, economic growth of an economy, a core variable in this study, is the growth rate at the mean income per capita, not the mean of the growth rate of income per capita. Ravallion (1998) points out that aggregation effects in growth regressions at the macro level may severely bias conventional tests and generate spurious impacts of inequality on economic growth.²

Last but not the least, authors have put forward several explanations for why income inequality might impact economic growth: the credit market imperfection channel (see, Galor and Zeira, 1993; Banerjee and Newman, 1993); the political economy channel (see, Alesina and Rodrik, 1994; Bertola, 1993; and Persson and Tabellini, 1994); and the socio-political instability channel (see, Alesina and Perotti, 1994; Gupta, 1990; Perotti, 1996). However, there are few studies to

² Ravallion (1998) investigates the impacts of asset inequality on consumption growth regression under the Cass-Koopmans-Ramseys framework at both household level and aggregate level. In his analysis, two assumptions should be met when examining the effects of inequality on growth: first, there is no underlying spatial externalities of average wealth; second, the change of consumption inequality should be white noise. Violations of these assumptions may lead to spurious effect of inequality.

support any of these transmission channels with their empirical results.³ Wrong remedies might be implemented to deal with the trend of increasing income inequality if policy makers do not know how income inequality affects economic growth exactly. For example, if the political economy channel is predominant, income inequality may retard economic growth in part because the efforts on redistribution caused by the unequal society themselves exert distortionary effects on growth. In this case, taxes and transfers may be exactly inappropriate policies (Ostry *et al.*, 2014).

In order to test the potential transmission mechanisms, micro data from a single country is needed. Due largely to the lack of such data, to the best of my knowledge, there is no such empirical work. This chapter contributes to the literature and fits in this research gap. First, a mathematical example is provided to demonstrate the problems of aggregating data when ignoring the curvature of the micro growth function. Next, by using Chinese Household Income Project (CHIP) survey data, this chapter verifies the predictions from the mathematical example. In addition, the current study will compare the estimation results both at the aggregate (village) level to the ones at the micro (household) level, in the hope of providing new empirical evidence for examining mainstream transmission mechanisms from a household perspective.

The estimation results show that at the macro level, a one percentage point increase in the Gini coefficient will lead to a 0.75 percentage point decrease in village income growth. At the micro level, empirical evidence shows that household income growth is a quadratic function of initial household income level and that no spill-over effect from village income inequality exists. Both results confirm the prediction from the mathematical example. In addition, combining the empirical results from both micro and macro level, it is suggested that the political economy channel is predominant in rural China.

The remainder of the current study is organized as follows. The second section provides a mathematical example and discusses how the specification of the micro

³ There are some exceptions. Perotti (1996) examines all the discussed channels.

growth function matters when investigating the inequality-growth nexus with macro data. The following section is a brief review of the mainstream transmission mechanisms of inequality-growth nexus, and discusses how they might apply to rural China. Section 4.4 describes the empirical strategy and discusses the predicted estimation results. Section 4.5 provides information of the data, while section 4.6 shows empirical evidence at both household and village level and discussion. The last part concludes and outlines policy implications.

4.2 Mathematical Example

In traditional growth empirics, it is normal to examine a growth function including a measure of initial income level on the right-hand-side in hope of examining the catch-up effect (or known as economic convergence). If the coefficient of initial income is statistically negative, it can be concluded that the growth for the poor is faster than their rich counterparts. However, the assumption that economic growth is linearly correlated to initial income might be too restrictive and ignore other shapes (or curvatures) of the growth function. If this assumption does not hold, the problem of misspecification regarding the growth regression may raise. This section provides a simple mathematical example to demonstrate this issue by introducing a quadratic term of initial income to the growth function. Other cases of different curvatures regarding the household income growth function are discussed in the Appendix 4C.

Suppose that in village v , there are only two households ($H = 2$) and each household has only one resident in every period ($n_1^h = n_2^h = 1$), therefore the total population (N^v) of village v is 2. The initial level of household income per capita for h_1 ($(y_1^h)_{-1}$) and h_2 ($(y_2^h)_{-1}$) are identical as Y . To monitor the impact of income inequality on economic growth, it is assumed that there is a mean-preserving income transfer from household h_1 to household h_2 by the non-zero amount of σ . After the income transfer, h_1 has $Y - \sigma$, while h_2 has $Y + \sigma$, enlarging the degree of income inequality ($Gini^v > 0$). It is worth noting that σ is standard deviation in this case, measuring the dispersion of household income per

capita from the mean after the income transfer. The larger the σ , the more unequal in this village.⁴

Equation 4.1 is growth regression where g^h is defined as growth rate of household income per capita. For capturing catch-up effect, it is assumed that the coefficient on the level of initial household income per capita (α_1) is negative, which suggests that poor families will have relatively higher income growth rate compared to their richer counterparts. In addition, following Barro (1991), this model also allows for a quadratic term of initial household income per capita and assumes that the change of household growth rate will be slower with the increase in initial income level ($\alpha_2 > 0$).⁵ Furthermore, for the purpose of simplicity, it is also assumed that there is no spill-over effect from income inequality at the household level, suggesting that the measure of income inequality does not enter the equation 4.1. This assumption will be verified in the empirical section of this chapter.

$$g^h(y^h) = \alpha_0 + \alpha_1 y^h + \alpha_2 (y^h)^2, \alpha_1 < 0, \alpha_2 > 0 \quad (4.1)$$

At the village level, growth rate of income per capita (g^v), conventionally, can be computed as the growth rate of the mean income per capita of village v . By plugging in all the settings and assumptions discussed above, after the income transfer, the village income per capita growth rate (equation 4.2) is not merely the growth rate of the mean household income per capita $g^h(\bar{y}^h)$, but also includes an extra term $\left(\frac{\alpha_1 + 3Y\alpha_2}{Y}\right)\sigma^2$.⁶

⁴ Gini coefficient in this case can be computed as $\frac{\sigma}{2Y}$. It is clear that Gini coefficient is positively correlated to the standard deviation σ in this case.

⁵ Barro (1991) also relaxes the linear assumption of the growth function. Although the coefficient of the quadratic term is positive, it is marginally significant with the t-value of 1.4 only. In empirical result section of this study, the assumption of $\alpha_2 > 0$ is affirmed.

⁶ Since the income growth rate for household can be expressed as $g^h = \frac{\Delta y^h}{y^h}$, then the household income change could be expressed as $\Delta y^h = y_i^h \times g^h$. Together with the assumption that $g^h(y^h) = \alpha_0 + \alpha_1 y^h + \alpha_2 (y^h)^2$, for h_1 , $\Delta y_1^h = \alpha_0(Y - \sigma) + \alpha_1 Y(Y - \sigma)^2 + \alpha_2 (Y - \sigma)^3$; for h_2 , $\Delta y_2^h = \alpha_0(Y + \sigma) + \alpha_1(Y + \sigma)^2 + \alpha_2(Y + \sigma)^3$. Therefore, the village growth rate could be computed as $g^v = \frac{\Delta y^v}{y^v} = \frac{\Delta \bar{y}^h}{\bar{y}^h} = \frac{\sum_{i=1}^H \Delta y_i^h}{\sum_{i=1}^H y_i^h} = \frac{\sum_{i=1}^H (y_i^h \times g^h)}{\sum_{i=1}^H y_i^h} = \frac{\alpha_0 Y(Y - \sigma) + \alpha_1 Y(Y - \sigma)^2 + \alpha_2 (Y - \sigma)^3 + \alpha_0 Y(Y + \sigma) + \alpha_1 Y(Y + \sigma)^2 + \alpha_2 (Y + \sigma)^3}{Y - \sigma + Y + \sigma} = \frac{\alpha_0 Y + \alpha_1(Y^2 + \sigma^2) + \alpha_2(Y^3 + 3Y\sigma^2)}{Y} = \alpha_0 + \alpha_1 Y + \alpha_2 Y^2 + \left(\frac{\alpha_1 + 3Y\alpha_2}{Y}\right)\sigma^2 = g^h(\bar{y}^h) + \left(\frac{\alpha_1 + 3Y\alpha_2}{Y}\right)\sigma^2$

$$\begin{aligned}
g^v &= \alpha_0 + \alpha_1 Y + \alpha_2 Y^2 + \left(\frac{\alpha_1 + 3Y\alpha_2}{Y} \right) \sigma^2 \\
&= g^h(\bar{y}^h) + \left(\frac{\alpha_1 + 3Y\alpha_2}{Y} \right) \sigma^2
\end{aligned} \tag{4.2}$$

To observe the relationship between σ and g^v , first order partial derivative with respect to σ has been practised as shown in equation 4.3. The computational result suggests that the sign of $\frac{\partial g^v}{\partial \sigma}$ depends on the curvature of the household growth function (α_1, α_2) , and the size of the mean household income level (Y). To one extreme, if no curvature of growth function $g^h(y^h)$ in equation 4.1 is allowed ($\alpha_2 = 0$), the output ($\frac{\partial g^v}{\partial \sigma} = \frac{2\alpha_1\sigma}{Y}$) of equation 3 will be a negative value, under the conditions that $\sigma > 0$, $Y > 0$, and $\alpha_1 < 0$. In other words, for the macro growth empirics, the conclusion of negative inequality-growth nexus might be purely caused by ignoring the non-linearity of initial income. Equation 4.3 clearly shows that the marginal effect of income inequality on economic growth could be positive with a large α_2 or Y .

$$\frac{\partial g^v}{\partial \sigma} = \frac{2\sigma}{Y} (\alpha_1 + 3\alpha_2 Y) \tag{4.3}$$

One important insight from this simple mathematical example is that, misspecification of the household income growth function might lead to misleading conclusion regarding the relationship between income inequality and growth at the macro level. This brings about a concern on existing literature focusing on inequality-growth nexus with macro level data: the findings of negative impacts of income inequality on growth might be purely driven by the assumption that household income growth is linearly correlated to its initial income level. Alternatively, as explained in this mathematical example, the negative inequality-growth nexus might not exist once curvature of growth function is introduced.

4.3 Why Might Village Inequality Affect Household Income Growth

There are several transmission mechanisms to explain that how income inequality would have impacts on economic growth. In the first class of explanations, Alesina

and Rodrik (1994), Bertola (1993), and Persson and Tabellini (1994) discuss the political economy that links income inequality and economic growth. At the macro level, the political economy channel works through political mechanism and economic mechanism. The first link illustrates that highly unequal income distribution would result in stronger needs for a higher redistributive tax rate in order to guarantee a more equal environment, which is mainly based on the median voter theorem proposed in Melzer and Richard (1981). Regarding economic mechanism, if policy makers levy a tax proportionally on one's physical and human capital endowments directly to meet the need of redistribution, it will lower the after-tax return on individual investments. This would bring about lower rates of aggregate capital accumulation, therefore impeding subsequent economic growth. In other words, it is the redistribution and tax policies that impede economic development through its distortionary impacts on investment in physical and human capital. Hence, in this sense, together with the effects from both mechanisms, income inequality is predicted to be negatively associated to growth.⁷ At the micro level, the redistribution policies caused by high inequality, might have different impacts depending on one's position of income distribution. Generally speaking, individuals who are located at the top of income distribution might be demotivated by the high tax rate because the after-tax return on individual investments will reduce significantly. Ideally, with the progressive taxation system, poor households will be better off through the redistribution.

The second explanation that links income inequality and economic growth is the socio-political instability channel (Alesina and Perotti, 1994; Gupta, 1990; Perotti, 1996). Unequal income distribution generates strong motivations for people, who pursue their interests outside from normal market, to engage in rent-seeking activities and social disrupting behaviours such as revolutions, crimes, or coups. The resulting political and social instability increase production costs, reduce protection of property rights, and undulate investment environment, therefore exerting adverse impacts on economic growth at the macro level.⁸ Also, socio-

⁷ Empirical evidence with cross-country data can be found in Perotti (1996).

⁸ Further theoretical discussion of the interplay between the socio-political instability, levels of wealth, and motivation for capital accumulation can be found in Benhabib and Rustichini (1996), and Rodrik (1999).

political unrest, caused by severe income disparity, might also result in greater pessimism for the future, therefore lead to less trust and social cohesion (Brown and Uslane, 2005). In this case, there will be more economic and social cost in economic activities, lowering productivity and economic efficiency, and therefore reducing economic growth. Similarly, at the micro level, high income inequality might redirect the resources to non-productive activities for the poor and the rich. For example, due to the fear from social unrest caused by high income inequality, the rich tend to invest more on security such as hiring body guards and lawyers. For the poor households, engaging in social disrupting behaviours also drive them away from normal productive activities, therefore deteriorating their income growth.

Several models (Galor and Zeira, 1993; Banerjee and Newman, 1993) emphasize the third transmission mechanism, which is referred as the credit market imperfection channel. Studies in this line stress that the cost of monitoring borrowers becomes higher due to asymmetric information in an imperfect credit market, which drives up the interest rate for borrowers. It is the stricter borrowing constraints in imperfect credit market that protect individuals, especially for the poor ones, from accessing to the loans against future income. If the initial level of inequality is high, then there will be more poor people who cannot access to loans due to stricter borrowing constraints, therefore lowering the aggregate level of investment and human capital accumulation, and resulting in lower economic growth rate. At the micro level, the impoverished households have limit access to loans as the under developed credit market, might potentially be stuck in ‘poverty trap’ and therefore have lower income growth.

These are, by no means, the only explanations to reveal the potential effects of income inequality on economic growth. However, these mechanisms might play important roles in explaining inequality-growth nexus under the context of rural China to some extent. In principle, all three mechanisms could have been in effect. Village is at the lowest tier of the rural administrative rank and its government plays important roles in providing public services such as education, healthcare, and infrastructure, which heavily determines the living standard and local household income opportunities. From the perspective of the political economy explanation, inequality at the village level may put pressure on local government to tailor related

village policies and therefore have effects on household income. Credit market imperfection might also be in effect as well. Although the economic reform since 1978 has brought about outstanding economic fruit, the credit and factor markets in rural area, so far, are still under developed (Benjamin, *et al.*, 2011). Regarding the socio-political instability, the unrest caused by inequality would cause waste of social resource and worsen the social cohesion, which is intuitive no matter at the village level or the national level.

4.4 Empirical Strategy

The previous empirical literature has found that income inequality is negatively associated to economic growth the macro level. However, through the mathematical example as discussed in section 4.2, the negative inequality-growth nexus might be invalid once certain level of curvature is introduced to the income growth function at the micro level. For instance, if the quadratic form of initial household income should be included in the household growth function, the impact from income inequality on aggregate income growth should be jointly determined by the degree of curvature and the initial averaged income at the micro level. To confirm this inference, the first task of this empirical research is to test the model (4.4), which is a household income growth function that contains both household income per capita and its quadratic form.

$$g_{i,t}^h = \beta_0 + \beta_1 y_{i,t-1}^h + \beta_2 y_{i,t-1}^{h^2} + \beta_3 Inequality_{j,t-1}^v + \beta_4 central + \beta_5 west + \varepsilon_{i,t} \quad (4.4)$$

g is growth rate of per capita income; y is the level of income per capita, the superscript ‘ h ’, stands for household level data while the subscripts ‘ i ’, ‘ t ’ are the labels for households and time, respectively. For instance, $g_{i,t}^h$ implies household income growth rate for household i at time t . In equation 4.4, it should be expected that $\beta_1 < 0$. This assumption is based on the economic convergence theory, also known as catch up effect in growth theory (Barro, 1991; Barro and Sala-i-Martin, 2004), which suggests that the growth rate for the poor tends to be faster than the rich. This is a common practice for majority of previous growth empirics (see, Barro, 2000; Forbes, 2000; Benjamin *et al.*, 2011). Corresponding to the

mathematical example, it is assumed that β_2 should be a positive value, suggesting that the income growth rate will drop slower with the increase in household income per capita.⁹ In addition, according to the mathematical example, it is also assumed that there is no spill-over effect from the income inequality at the village level, which implies that β_3 is expected to be not significantly different from zero.¹⁰ In equation 4.4, if both β_1 and β_2 are statistically significant and the corresponding signs meet the expectations, it suggests that the linear assumption regarding the household income growth function is not appropriate. Furthermore, with the computed average household income per capita \bar{y}^h and the estimated coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$ in equation 4.4, the direction of impacts from income inequality to income growth at the village level can be predicted with the equation 4.3.

The second task of this chapter is to verify this prediction via running regression 4.5 for two main reasons. First, it will offer a clear comparison between the estimation with data at different level (macro/micro) for the same specification. Second, due to the complex of non-linearity in equation 4.2, equation 4.5 offers a simplified version to monitor the association between the village income inequality and the village income growth. The research interest is focusing on the coefficient on the measure of village income inequality (γ_3). As discussed in the mathematical example, the sign of γ_3 should be the same as the computational result of $(\hat{\beta}_1 + 3\hat{\beta}_2 \times \bar{y}^h)$. Specifically, if the transmission mechanisms that are discussed in section 4.3 are in place at the macro level, it should be expected that γ_3 is negative.

$$g_{j,t}^v = \gamma_0 + \gamma_1 y_{j,t-1}^v + \gamma_2 y_{j,t-1}^{v^2} + \gamma_3 Inequality_{j,t-1}^v + \gamma_4 central + \gamma_5 west + \varepsilon_{j,t} \quad (4.5)$$

Similarly, g is growth rate of per capita income; y is the level of income per capita, the superscript ‘ v ’, stands for village level data while the subscripts ‘ j ’, ‘ t ’ are the label for village and time, respectively. The computation of g^v is the growth rate of

⁹ This is also following the practice of the growth empirics in Barro (1991).

¹⁰ This is the same as the equation 4.1, which assumes that there is no spill-over from the income inequality. Otherwise, if β_3 is significantly different from zero, then the assumption in 4.1 does not hold.

the mean value of the household income per capita within that village (y^v), the practice which is in accordance with the definitions in the previous mathematical example.

The third task of this chapter is to identify the transmission mechanisms, which is tested through the same regression at the macro level (equation 4.6) and at the micro level (equation 4.7), respectively. In addition to the equation 4.4 and 4.5, the new set of regressions (4.6 and 4.7) also include an interaction term of the household initial income and the measure of income inequality. If the abovementioned mechanisms are in place, it can be concluded that income inequality exerts adverse impacts on the subsequent economic growth at the macro level. In this case, the coefficient on the measure of income inequality for the equation 6 should be statistically significant and negative for all transmission mechanisms ($\theta_3 < 0$). However, to identify which mechanism is predominant, regression 4.7 should be of help. Based on the discussion in the section 4.3, given that $\theta_3 < 0$ in the equation 4.6, different coefficients on τ_3 , τ_4 in equation 4.7 will inform a specific transmission mechanism. Table 4-1 has provided the related predictions regarding different transmission mechanisms.

$$g_{j,t}^v = \theta_0 + \theta_1 y_{j,t-1}^v + \theta_2 y_{j,t-1}^{v^2} + \theta_3 Inequality_{j,t-1}^v + \theta_4 y_{j,t-1}^v \times Inequality_{j,t-1}^v + \theta_5 central + \theta_6 west + \varepsilon_{j,t} \quad (4.6)$$

$$g_{i,t}^h = \tau_0 + \tau_1 y_{i,t-1}^h + \tau_2 y_{i,t-1}^{h^2} + \tau_3 Inequality_{j,t-1}^v + \tau_4 y_{i,t-1}^h \times Inequality_{j,t-1}^v + \tau_5 central + \tau_6 west + \varepsilon_{i,t} \quad (4.7)$$

If the political economy channel (model 1) is in effect in rural China, it indicates that the rich will suffer from lower growth rate while the poor will be better off through the redistribution caused by the high level of income inequality. In an extreme case, when one has zero initial income, then the interaction term should become zero as well. Therefore, the expectation of $\tau_3 > 0$ is to make sure this poor man is better off after redistribution. In the socio-political instability channel (model 2), the impacts of income inequality can be treated as negative externality since it is harmful to everyone regardless the position in income distribution.

Therefore, if the socio-political instability is predominant, the sign on the coefficient of income inequality should be negative. However, the sign on the interaction term is uncertain since the exact impacts from income inequality to the rich and to the poor are unclear. If the imperfect credit market channel (model 3) is in place, then it should be expected that the coefficients on the measure of income inequality are statistically insignificant. As discussed in the credit market imperfection, the initial poor will be stuck in the poverty trap. In equation 4.7, since the initial household income has been controlled, if the coefficient on the measure of income inequality, it suggests that other factors besides imperfect credit market should be sources of the relationship.¹¹

Table 4-1. Predictions for Different Mechanisms for Micro Regression

Model	Transmission Mechanisms	Expected signs
1	Political Economy	$\tau_3 > 0, \tau_4 < 0$
2	Socio-political Instability	$\tau_3 < 0$
3	Credit Market Imperfection	$\tau_3 = 0$

Note: Expected signs of the coefficients are referred to the equation 4.7.

Location dummy variables in all regressions are ‘*central*’ and ‘*west*’, with the baseline as ‘*east*’, indicating the central China, Western China, and Eastern China, respectively. Consistent with most of the existing growth empirics on China, the provinces in three categories are demonstrated in Figure 4-1. The provinces in west of China are known as less developed areas, which are highlighted in dark in the Figure 4-1, while the richest regions, the east or the costal part of China, are coloured in light grey in the same figure. The remaining part should be the central China. It should be expected that the coefficients on location dummies are negative, indicating that both economic growth in western and central China are slower than the ones in eastern China.¹²

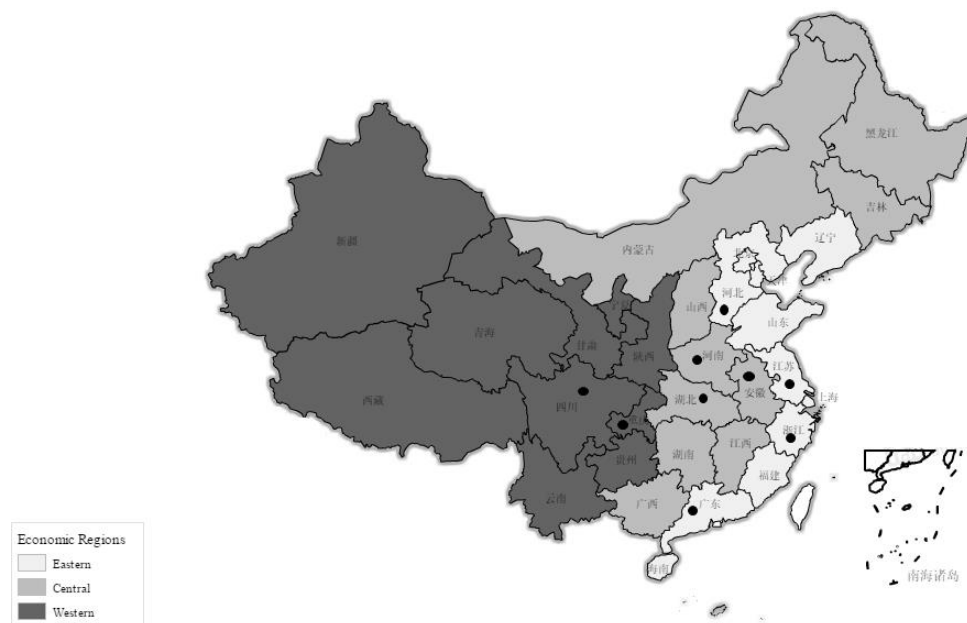
¹¹ This practice is also employed in Benjamin *et al.* (2011) for testing the imperfect credit market channel.

¹² Conventionally, Chinese provinces can be divided into three categories based on their economic development, namely western, eastern and central. The richest provinces are from the eastern of China, they are Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shanghai, Shandong, Tianjin and Zhejiang. The less developed provinces are from the western of China, they are Chongqing, Guizhou, Gansu, Ningxia, Qinghai, Sichuan, Shaanxi, Xinjiang, Xizang (Tibet), and Yunnan. The remaining provinces should belong to the central region, including Anhui, Guangxi, Henan, Heilongjiang, Hunan, Hubei, Jiangxi, Jilin, Inner Mongolia, and Shanxi.

4.5 Data and Key Variables

The data used in the current chapter is mainly derived from CHIP, which was initiated by researchers from Beijing Normal University and Australian National University, and is supported by the China National Bureau of Statistics (NBS), and the Institute for the Study of Labour (IZA). The surveys were implemented by NBS through a series of face-to-face questionnaire-based interviews, covering both rural and urban areas in China in 1988, 1995, 2002, 2007, 2008, 2013. CHIP collects data at both individual and household level, including sources of incomes and expenditures, employment status, education level, and social and economic characteristics.

Figure 4-1. Economic Regions in China



Note: The provinces covered in the sample are marked by dots.

Even though six waves of CHIP are available already, I will use only CHIP2007 and CHIP2008 in this chapter because the survey traced the same individuals and households in these two waves. This is of extreme importance since income growth, the dependent variable in equation 4.4, needs the information of the income level for the same households in each period. This requires panel data, instead of

repeated cross section data. In this study, income growth is computed by the ratio between the change of income from 2007 to 2008, to the income level in 2007.¹³

In addition, this chapter will only employ data from rural China. For some transmission channels, there are significant differences between the rural and urban residents. For example, if I consider the whole sample combining both rural and urban household, the fact that the development of credit market in urban areas is significantly better than in rural areas will be ignored, and therefore may lead to misleading estimation results. All in all, data collected in CHIP2007 and CHIP2008 include more than 8000 rural households in each wave, covering about 350 villages from nine provinces in China. The selected provinces in CHIP2007 and CHIP2008 are marked as dots on the map in Figure 4-1, including Jiangsu, Zhejiang, and Guangdong from eastern China; Anhui, Hebei, Henan, and Hubei from central China; Chongqing and Sichuan from western China.

Before the estimation, several definitions should be further explained clearly. First, the definition of household in CHIP survey is based on Chinese residency and registration (hukou system). Second, regarding the definition of income, I will use gross income (e.g. wage income, income from family-run business) for each household member. Also, the calculation of income inequality index and income growth are based on the same definition of the household income per capita as well. With respect to the measure of income inequality, I will initially use Gini coefficients and then use Theil index and Mean-log-deviation as a robustness check for the estimation results.¹⁴

Table 4-2 provides the descriptive statistics including the mean, standard deviation, and quantiles of key variables at the household level (panel I) and village level

¹³ $growth = \frac{\Delta y}{y} = \frac{y_{2008} - y_{2007}}{y_{2007}} \times 100$, where y is the income level.

¹⁴ Gini coefficient is the most popular measure of income inequality, which is calculated by $Gini = \frac{1}{n} (n + 1 - 2(\frac{\sum_{i=1}^n (n+1-i)y_i}{\sum_{i=1}^n y_i}))$, where n and y are number of household for each village, and household net income per capita. The other two measures are from the generalized entropy measures, which can be formulated as $GE(\alpha) = \frac{1}{\alpha(\alpha-1)} \left[\frac{1}{N} \sum_{i=1}^N \left(\frac{y_i}{\bar{y}} \right)^\alpha - 1 \right]$. α is the weight given to the distances between incomes at different parts of the income distribution. $GE(0)$ is mean-log-deviation and $GE(1)$ is Theil index in this chapter. With a lower α , $GE(\alpha)$ becomes more sensitive to changes for the bottom percentile in the income distribution.

(panel II), respectively. At the household level, except for the income per capita at 10th percentile, the income per capita in other positions of the distribution increased slightly. For example, the mean income per capita boosted from 5293 yuan in 2007 to 5924 yuan in 2008 (12% higher). It is worth noting that the poorest 10th percentile, as shown in Table 4-2, has zero income per capita in both observed periods. This might be caused by the unresponsive interviewees. In other words, part of the interviewees did not report (or report only in one year) their income information.¹⁵ With respect to the income per capita growth rate, the mean is 110%, significantly higher than the 90th percentile of 96%. Further, considering this to the fact that the income growth rate for the 50th percentile is 0, it can be inferred that the growth rate of super rich (posited above 90th percentile) is high.

Table 4-2. Sample Summary Statistics

	Year	Mean	Std. Dev.	Obs.	Percentiles		
					10th	50th	90th
<u>I. Household-level Data</u>							
Income pc.	2007	5293.16	6781.58	7984	0	4500	12000
(Yuan)	2008	5924.77	7747.97	7971	0	4800	12600
Growth (%)		1.10	30.54	5528	-1.00	0.00	0.96
<u>II. Village-level Data</u>							
Income pc.	2007	5347.88	3725.79	355	1735.39	4700.00	9175.39
(Yuan)	2008	6071.89	5488.43	353	2089.93	4877.78	11384.62
Growth (%)		0.20	0.60	346	-0.32	0.08	0.84
Gini	2007	0.25	0.09	348	0.15	0.25	0.34
Coefficient	2008	0.26	0.10	347	0.15	0.26	0.36
Mean-log-	2007	0.14	0.11	348	0.04	0.12	0.25
deviation	2008	0.14	0.11	347	0.04	0.12	0.26
Theil index	2007	0.13	0.10	348	0.04	0.11	0.20
	2008	0.14	0.12	347	0.04	0.11	0.25

Note: The currency listed in this table is Chinese Yuan. The America Dollar (USD)-Chinese Yuan (CNY) exchange rate in 2008 was around 1 USD=6.95CNY.

Regarding the aggregate data at the village level, in general, income per capita in each category increased slightly from 2007 to 2008. However, the income

¹⁵ In the raw CHIP data, the genuine unresponsive interviewees will leave the income as missing value, which will not be considered in the sample. However, some might want to underreport their income and leave it as 0 income. Since there is no way to distinguish who genuinely earns 0 income. I cannot treat every respondent reporting 0 income as unresponsive interviewee in this case. Instead, I keep them all in the sample.

distribution at the macro level seems more equal compared to the case with household level data. For example, income per capita for 10th and 50th percentiles are higher at the village level than the ones in household level, while the income per capita for the rich (90th percentile) at the village level is relatively lower. Similar pattern can be found regarding the village income growth rate. The mean of village income growth rate is about 20% annually. But the rich villages (the 90th percentile) growth much faster than the average level with the rate of 84%. With respect to the measures of income inequality, they show a slight increase from 2007 and 2008. The mean of Gini is around 0.25, indicating a low level (or acceptable level) of income disparity in observed sample. Gini is as low as 0.15 for 10th percentile, just less than half of the worst part, 0.34 for 90th percentile. Mean-log-deviation and Theil index show the similar trends.

4.6 Estimation Results

Table 4-3 summarizes the empirical results regarding equation 4.4 to 4.7, including the analysis at both micro and macro level. The empirical results of the robustness checks with different measure of income inequality are provided in the Appendix Table 4A-1 (with mean-log-deviation) and Table 4A-2 (with Theil index). Each column in Table 4-3 contains empirical results corresponding to their regression models that have been discussed in previous section. The first column contains the related explanatory variables for each regression, which is in accordance to their corresponding level of data (household/village). All results are derived from the ordinary least squares (OLS). For the regressions at the village level (equation 4.4 and 4.7), the standard errors are corrected by clustering the village. For better understanding the impact of income inequality on subsequent economic growth, variables of growth, and Gini coefficients are rescaled as percentage, and the unit for village income is in hundred Chinese Yuan.¹⁶

The estimation results for the regression 4.4 is shown in the column (i) in Table 4-3. The coefficients on $y_{i,t-1}^h$ and $y_{i,t-1}^{h^2}$ are statistically significant at 5% level and have the expected signs, suggesting that although the household growth rate will be

¹⁶ Since the value of income inequality lies between 0 and 1, it is common to use Gini coefficient as percentage in empirical studies. But in this chapter, the mean-log-deviation and Theil index will not be rescaled.

lower with the increase of income, the rate of decreasing will be slower during this process. In addition, as assumed, the coefficient on the measure of income inequality is not significantly different from zero, implying that there is no spill-over effect from income inequality at the household level. As demonstrated in the mathematical example, since the household income growth function is not purely a linear relationship to initial household income, the association between income inequality and income growth at village level might not be negative. According to equation 4.3, the sign of marginal effect of income inequality on growth should be jointly determined by the curvature of the household income growth function and the initial average household income. Given the results of equation 4.4 and the descriptive statistics in Table 4-2, it can be computed that $(\hat{\beta}_1 + 3\hat{\beta}_2 \times \bar{y}^h) < 0$, predicting that income inequality is negatively associated to the village income growth in rural China.¹⁷ This prediction is verified by the equation 4.5, the results of which has been shown in column (ii) in Table 4-3.

Similar to the household income growth function, the growth function at the village level also shows certain concavity given that the signs on coefficients γ_1 and γ_2 are the same as the ones in β_1 and β_2 , and are statistically significant at even 1% level. The research interest is focusing on the coefficient of income inequality measure, which is -0.75 and significant at 5% level. It implies that about one percentage point increase in Gini coefficient is associated to 0.75 percentage point decrease in village income growth. Such adverse correlation confirms the prediction computed with the household level estimation results. Also, this finding supports the previous empirical literature. It is worth noting that from the estimation results both equation 4.4 and equation 4.5, not all location dummies have expected empirical results. While the coefficient on central is not significant at all, the coefficients on west are negative and significant, indicating that the income growth in central rural China and eastern rural China has no different but the one in western area is significantly lower.

Given the estimation results from equation 4.5 that income inequality is adversely correlated to village income growth, the next question is: which transmission

¹⁷ $\hat{\beta}_1 = -11.188, \hat{\beta}_2 = 0.030, \bar{y}^h = 52.9$

mechanism could potentially explain this inequality-growth nexus in rural China? The last two columns of Table 4-3 are estimation results for the regression 4.7 and 4.6, respectively. At the village level, with the additional interaction term between income inequality and initial income per capita in equation 4.6 (column iv), the empirical results do not change significantly compared to the ones in regression 4.5. However, the interaction term is not significantly different from zero, suggesting that the negative impacts of income inequality do not vary with the development of the village. At the household level (column iii), the coefficient on the measure of income inequality is positive while the one on the interaction term is negative, suggesting that village level income inequality is actually in favour of the poor household, but harmful to the rich. Both coefficients are significant at 10% level. In general, both results of regression 4.6 and 4.7 show that the growth rates in western China are significantly lower than the ones in eastern China, but there is not significant difference between central China and the eastern. Combining the empirical results from regression 4.6 ($\theta_3 < 0$) and regression 4.7 ($\tau_3 > 0, \tau_4 < 0$), it seems that the theories of political economy channel is potentially predominant when explaining the negative inequality-growth nexus in rural China.

Table 4-3 Estimation Results for Model 4.4 – 4.7

Independent Variables	Inequality Measure: Gini Coefficient			
	(i)	(ii)	(iii)	(iv)
y_{t-1}	-11.188** (4.443)	-0.880*** (0.168)	-4.447* (2.411)	-1.099*** (0.240)
y_{t-1}^2	0.030** (0.012)	0.003*** (0.001)	0.038** (0.016)	0.003*** (0.001)
$Inequality_{t-1}^v$	6.311 (4.181)	-0.750** (0.359)	28.448* (15.591)	-1.175** (0.488)
$y_{t-1} \times Inequality_{t-1}^v$	-	-	-0.286* (0.156)	-0.008 (0.006)
<i>central</i>	-0.387 (105.412)	-7.673 (7.100)	-0.901 (105.551)	-7.352 (7.097)
<i>west</i>	-181.229** (88.891)	-18.689** (8.689)	-174.08** (86.203)	-17.949** (8.699)
Constant	567.116** (224.965)	81.632*** (11.104)	-14.093 (233.628)	92.902*** (14.149)
Data Level	Household	Village	Household	Village
Equation	4.4	4.5	4.7	4.6
R-square	0.007	0.108	0.009	0.113
N	5528	346	5528	346

Note: Standard errors are reported in brackets. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level. Household (village) in Data Level row indicates the regression are examined with household (village) level data. The standard errors are corrected by clustering the village and are shown in the parentheses for the estimations at the household level. The dependent variable is growth rate of income. Both growth rate and Gini coefficients are rescaled in percentage while the income per capita is rescaled in hundred.

4.7 Discussion

It is obvious that estimation results from micro and macro level regressions are inconsistent: while the macro regression shows that income inequality is negatively associated to the subsequent income growth, the micro regression results do not support this finding with household data. If a policy maker solely believes in the results derived from macro empirical evidence, he/she will make completely wrong remedies against income inequality.

Why are the outcomes so different? One possible explanation is aggregation effect. Ravallion (1998) is the first study to point out that macro data might misreport the true relationship and generate spurious impacts of inequality on growth. In this chapter, aggregation effect will be in place when macro data is not purely the mean value from the micro data. These variables, in current study, include the squared initial income per capita, and income growth. Appendix 4B has illustrated how

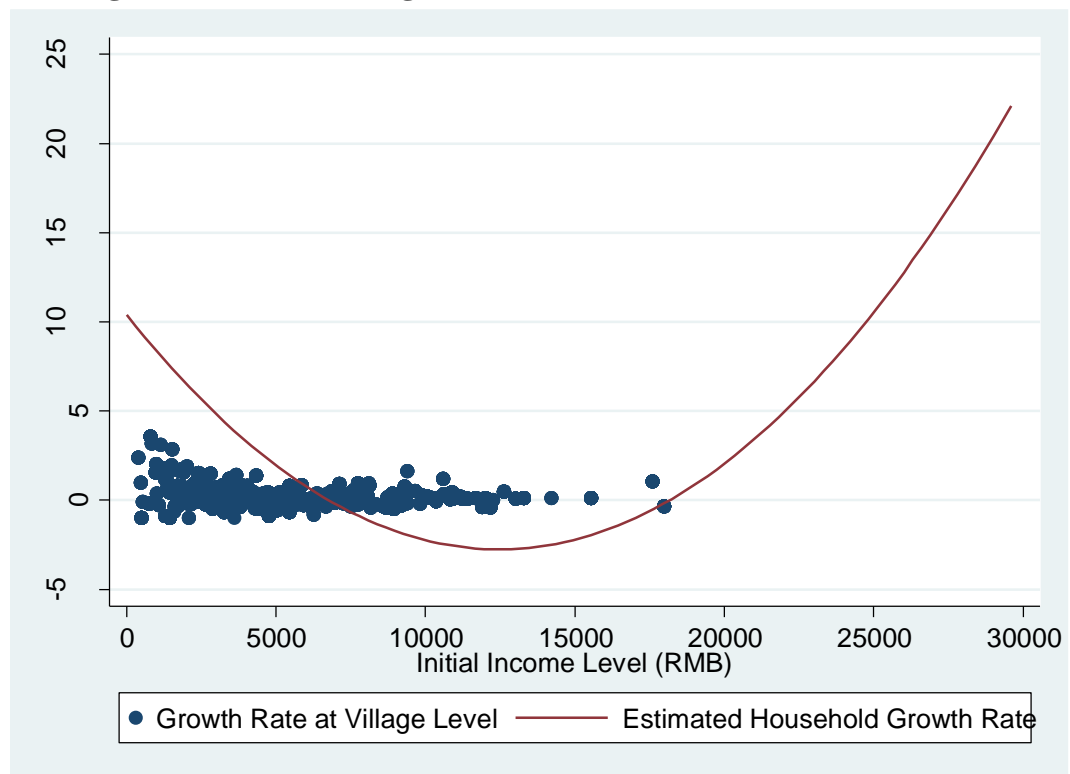
growth rate at the aggregate level and aggregate squared initial income level are not simply the mean of their micro corresponding values.

To demonstrate the aggregate effect, figure 4-2 depicts the differences in growth rates with macro and micro data. The horizontal axis is the level of initial income per capita while the vertical axis is the income growth rate. Particularly, the dots in figure 2 are the income growth rate for villages against its corresponding initial village income per capita. If the household initial incomes are identical across village (the extreme income equality), then the growth at the macro level is exactly the mean of the growth income. In other words, if there is no initial income variation in the villages, then the dots in the figure 4-2 should be on the quadratic fit of the household income-growth function. In this case, then aggregating the data at the macro level would not cause any trouble.

The aggregation effect will raise when there are variations of initial income among households. As shown in the figure 4-2, the economic growth at the village level (shown as blue dots) are spreading around zero and less diverse because the household income variations are averaged at the macro level. In addition, it is also worth to note that the blue dots (village economic growth rates) are not always lower than the predicted household income growth, implying that the actual direction of the error when aggregating the household level data is uncertain.¹⁸ It is suggested in the figure 4-2 that the village economic growth is overall lower once the household level income is aggregated because the majority of the dots are laying under the predicted household income growth. This will be mistakenly counted as the adverse impacts of income inequality, if policy makers do not realize the existence of aggregation effect. As a result, the negative impact of income inequality on economic growth (if it exists) might be amplified by aggregate effect.

¹⁸ Further discussions are provided in the Appendix B.

Figure 4-2. Actual Village Growth vs. Predicted Household Growth



Note: The scatter plots are the income growth rate to the initial income per capita at the village level. The curve is the quadratic fit of the household initial income level and income growth. The horizontal axis is the initial income per capita while the vertical axis is the income growth rate.

To sum up, the whole discussion of this subsection delivers a message for the macro empirics focusing on inequality-growth nexus. Even if the specification of the growth function is correct, the aggregation effect still would cause errors that will be mistakenly taken into account as the impacts of income inequality on growth.

4.8 Conclusion

Is income inequality harmful to economic growth? This question has long been one of the core research questions among politicians, economists, and sociologists. Although majority existing empirical paper conclude that the impacts of income inequality on economic growth are negative, these studies might ignore the problems with aggregate data, namely, aggregate effects and the non-linearity of micro growth function. If these issues are not considered when using aggregate data, the adverse impacts of income inequality that have been found in previous

empirical literature might be spurious. This chapter intends to answer this question with micro data in hope of addressing with the potential concerns on macro data.

To confirm the concerns of macro data, the current study explores the effects of income inequality on economic growth at both micro (household) level and macro (village) level, with Chinses Household Income Project survey data. Similar to most of the existing literature, the estimation results with macro data show that the income inequality exerts adverse effect on economic growth. However, the estimation results obtained from micro data tell another story: the coefficients of income inequality are positive and statistically significant. In addition, this positive effect will be impaired with the increase of initial household income level.

Specifically, the households whose initial income per capita is greater than 9947 yuan will suffer from the adverse effects of income inequality, while the ones who live below this threshold will have a better income growth, keeping other factors unchanged. This result suggests that income inequality in rural China is an income growth driver for majority of the rural dwellers since the threshold (9947 yuan) is much higher than the mean of the household income per capita. In addition, combining the empirical evidence from both macro and micro regressions, they suggest that the political economy mechanism (as discussed as model 1 in Table 4-1) is predominant in rural China, and taxes and transfers are exactly the inappropriate policies, which has been discussed in (Ostry *et al.*, 2014).

Given two identical villages except for different degrees of income inequality, if you want to have a higher income growth, which village should you live in? Based on the empirical results from this chapter, you will find that it is more depended on how much you earn at the moment. According to the economic convergence theory, although high initial income will lead to a relatively lower income growth, but it will be even slower in the village with higher income inequality. On the other hand, for the low initial household income, one's income growth will be accelerated in the village with higher income inequality. Instead, for policy makers, it is extremely important to notice the potential errors brought by the misspecification and aggregation effect. Ideally, combining both macro and micro empirical evidence will provide with a clearer picture of inequality-growth nexus.

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Appendix 4A. Robustness Checks with Different Measures on Inequality

Table 4A-1 Estimation Results for Model 4.4 – 4.7 with Mean-log-deviation

Independent Variables	Inequality Measure: Mean-log-deviation			
	(i)	(ii)	(iii)	(iv)
y_{t-1}	-10.255** (4.106)	-0.948*** (0.165)	-2.485 (2.200)	-0.964*** (0.192)
y_{t-1}^2	0.026** (0.011)	0.003*** (0.001)	0.045** (0.019)	0.003*** (0.001)
$Inequality_{t-1}^v$	2576** (1126.1)	-25.786 (30.089)	7799.61** (3452.751)	-31.334 (44.502)
$y_{t-1} \times Inequality_{t-1}^v$	-	-	-66.900** (31.127)	0.082 (0.486)
<i>central</i>	-46.270 (104.278)	-8.659 (7.135)	-38.004 (102.053)	-8.639 (7.146)
<i>west</i>	-140.430* (75.244)	-20.182** (8.700)	-109.862 (69.098)	-20.148** (8.715)
Constant	318.030** (145.204)	69.935*** (9.295)	-447.321 (289.948)	70.885 (10.867)
Data Level	Household	Village	Household	Village
Equation	4.4	4.5	4.7	4.6
R-square	0.013	0.099	0.028	0.099
N	5528	346	5528	346

Note: Standard errors are reported in brackets. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level. Household (village) in Data Level row indicates the regression are examined with household (village) level data. The standard errors are corrected by clustering the village and are shown in the parentheses for the estimations at the household level. The dependent variable is growth rate of income. Growth rates are rescaled in percentage while the income per capita is rescaled in hundred.

Table 4A-2 Estimation Results for Model 4.4 – 4.7 with Theil Index

Independent Variables	Inequality Measure: Theil Index			
	(i)	(ii)	(iii)	(iv)
y_{t-1}	-11.278** (4.490)	-0.924*** (0.166)	-10.370** (4.078)	-0.978*** (0.180)
y_{t-1}^2	0.031** (0.013)	0.003*** (0.001)	0.037** (0.015)	0.003*** (0.001)
$Inequality_{t-1}^v$	286.073 (215.098)	-40.964 (30.949)	1494.092* (872.399)	-72.433 (50.599)
$y_{t-1} \times Inequality_{t-1}^v$	-	-	-13.525** (7.906)	-0.322 (0.410)
<i>central</i>	4.431 (105.003)	-8.473 (7.111)	-2.014 (105.041)	-8.209 (7.123)
<i>west</i>	-182.679** (89.717)	-19.952** (8.689)	-177.276** (87.847)	-19.733** (8.698)
Constant	701.270** (281.562)	70.173 (9.015)	561.426** (229.652)	74.469*** (10.554)
Data Level	Household	Village	Household	Village
Equation	4.4	4.5	4.7	4.6
R-square	0.007	0.102	0.008	0.103
N	5528	346	5528	346

Note: Standard errors are reported in brackets. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level. Household (village) in Data Level row indicates the regression are examined with household (village) level data. The standard errors are corrected by clustering the village and are shown in the parentheses for the estimations at the household level. The dependent variable is growth rate of income. Growth rates are rescaled in percentage while the income per capita is rescaled in hundred.

Appendix 4B. Deficiency in Data at Aggregate Level

This section shows the deficiency in macro data when aggregating from its micro raw data for certain variables. In this chapter, the economic growth rate at the village level is computed as shown in the equation 4B.1, while the quadratic form of initial income level is calculated via equation 4B.2.

$$g^v = \frac{\Delta y^v}{y^v} = \frac{\Delta \bar{y}^h}{\bar{y}^h} = \frac{\sum_{i=1}^H \Delta y_i^h}{\sum_{i=1}^H y_i^h} = \frac{\sum_{i=1}^H (y_i^h \times g^h)}{\sum_{i=1}^H y_i^h} \neq \sum_{i=1}^H \frac{\Delta y_i^h}{y_i^h} \quad (4B.1)$$

$$(y^v)^2 = (\bar{y}^h)^2 = \left(\frac{\sum_{i=1}^H y_i^h}{H} \right)^2 \neq \sum_{i=1}^H \frac{(y_i^h)^2}{H} \quad (4B.2)$$

Where the superscript v denotes the variables are aggregated at the village level; h denotes the variables are the data at the household level; H is the number of households in the village; g is the economic growth and y is initial income level; operator Δ computes the change between t and $t-1$. The equation 4B.2 also requires the assumption that the number of household member is identical across households and do not change overtime.

Generally, the aggregated data should be the mean of its corresponding variables. One example is the initial income level of village, which could be obtained from the mean of the initial household income level. However, for the variables of economic growth and the quadratic term of village initial income level, as shown in 4B.1 and 4B.2, they are not purely the mean of their values at the household level, under the condition that the initial incomes of household are not identical across the village. This will bring errors to the estimation regression. These errors when aggregating data from household level, in the current research, are referred as aggregation effect, which is believed to be one of the factors that contributes to conflicting empirical results from micro and macro data. However, it is worth to note that the direction of the error is unclear.

Appendix 4C. Various Curvature of Household Income Growth Function

To illustrate that the impacts of income inequality are sensitive to the curvature of the household income growth function, this section will introduce three cases with various curvature regarding the household income function. As discussed in the chapter, the fundamental settings of mathematical example also apply to the rest of discussion in this section. Suppose that in village v , there are only two households ($H = 2$) and each household has only one resident in every period ($n_1^h = n_2^h = 1$), therefore the total population (N^v) of village v is 2. The initial level of household income per capita for h_1 ($(y_1^h)_{-1}$) and h_2 ($(y_2^h)_{-1}$) are identical as Y . To monitor the impact of income inequality on economic growth, it is assumed that there is a mean-preserving income transfer from household h_1 to household h_2 by the non-zero amount of σ . After the income transfer, h_1 has $Y - \sigma$, while h_2 has $Y + \sigma$, enlarging the degree of income inequality ($Gini^v > 0$). It is worth noting that σ is standard deviation in this case, measuring the dispersion of household income per capita from the mean after the income transfer. The larger the σ , the more unequal in this village. At the village level, growth rate of income per capita (g^v), conventionally, can be computed as the growth rate of the mean income per capita of village v , which is shown as the equation 4C.1.

$$g^v = \frac{\Delta y^v}{y^v} = \frac{\Delta \bar{y}^h}{\bar{y}^h} = \frac{\sum_{i=1}^H \Delta y_i^h}{\sum_{i=1}^H y_i^h} = \frac{\sum_{i=1}^H (y_i^h \times g^h)}{\sum_{i=1}^H y_i^h} \quad (4C.1)$$

Case 1. A less curved case

If the household growth income function is given as the equation 4C.2, which does not allow any degree of curvature at all in the growth regression, the aggregate income growth at the village level should be expressed as the equation 4C.3. It is not merely the growth rate of the mean household income per capita $g^h(\bar{y}^h)$, but also includes an extra term $-\frac{\sigma^2}{Y}$. By taking the first order partial derivative with respect to σ to the village income growth (4C.3), the result (4C.4) suggests the sign of income inequality is negative. It implies that the impact of income inequality is

negatively associated to the aggregate income growth, which is consistent to majority of traditional empirical literature.

$$g^h(y^h) = \alpha_0 - y^h \quad (4C.2)$$

$$g^v = \frac{\sum_{i=1}^H (y_i^h \times g^h)}{\sum_{i=1}^H y_i^h}$$

$$= \frac{[\alpha_0 - (Y - \sigma)](Y - \sigma) + [\alpha_0 - (Y + \sigma)](Y + \sigma)}{Y - \sigma + Y + \sigma} \quad (4C.3)$$

$$= \frac{\alpha_0 Y - Y^2 - \sigma^2}{Y} = g^h(\bar{y}^h) - \frac{\sigma^2}{Y}$$

$$\frac{\partial g^v}{\partial \sigma} = -\frac{\sigma^2}{Y} < 0 \quad (4C.4)$$

Case 2 A threshold case

If certain curvature is allowed to be considered in the household income growth function, such as the equation 4C.5, through the similar analysis to the case 1 (4C.6), village income growth equal to the growth rate of mean household income. By computing the partial effects of income inequality (4C.7), it can be concluded that income inequality has no impact on village income growth, if the household growth function is specified as equation 4C.5.

$$g^h(y^h) = \frac{\alpha_0}{y^h} \quad (4C.5)$$

$$g^v = \frac{\sum_{i=1}^H (y_i^h \times g^h)}{\sum_{i=1}^H y_i^h}$$

$$= \frac{\frac{\alpha_0}{Y - \sigma} * (Y - \sigma) + \frac{\alpha_0}{Y + \sigma} * (Y + \sigma)}{Y - \sigma + Y + \sigma} \quad (4C.6)$$

$$= g^h(\bar{y}^h) = \frac{\alpha_0}{Y}$$

$$\frac{\partial g^v}{\partial \sigma} = 0 \quad (4C.7)$$

Case 3 A more curved case

If the household growth function is given as equation 4C.8, then the income growth at the village level can be expressed as 4C.9. By taking the first order condition with respect to σ , the result in 4C.10 shows that income inequality is positively associated to the village income growth.

$$g^h(y^h) = \frac{\alpha_0}{(y^h)^2} \quad (4C.8)$$

$$g^v = \frac{\sum_{i=1}^H (y_i^h \times g^h)}{\sum_{i=1}^H y_i^h} = \frac{\frac{\alpha_0}{Y-\sigma} + \frac{\alpha_0}{Y+\sigma}}{Y-\sigma + Y+\sigma} = \frac{\alpha_0}{Y^2 - \sigma^2} \quad (4C.9)$$

$$\frac{\partial g^v}{\partial \sigma} = \frac{2\sigma\alpha_0}{(Y^2 - \sigma^2)^2} > 0 \quad (4C.10)$$

Table 4C-1 summarizes the results for all three cases with different assumptions on the household income growth function. It clearly shows that the change of income growth rate at the village level is sensitive to the curvature of household income growth function. Particularly, when the household income growth is inverse to the initial household income per capita, the change in income inequality has no effects on the village economic growth at all (case 2). If the household income growth function is less curved as specified in case 1 (more curved as specified in case 3), then an increase in income inequality will lead to a decrease (increase) in village economic growth.

Table 4C-1. Summary of All Cases with Various Curvature on Growth Function

Case	Household Growth Function	Curvature	$\frac{\partial g^v}{\partial \sigma}$	Results
1	$\alpha_0 - y^h$	less curved	$-\frac{\sigma^2}{Y} < 0$	Decreased
2	$\frac{\alpha_0}{y^h}$	threshold	0	unchanged
3	$\frac{\alpha_0}{(y^h)^2}$	more curved	$\frac{2\sigma\alpha_0}{(Y^2 - \sigma^2)^2} > 0$	Increased

Chapter 5. Less is More? An Evaluation of the One-Child Policy on Fertility and Education

5.1 Introduction

Chapter 4 has examined three transmission mechanisms with the village (macro) and household (micro) level data and shown that the political economy channel is predominant in rural China.¹ However, as introduced in the literature review chapter, there is another possible channel that could explain the negative impacts of income inequality on economic growth in rural China, which is rarely tested in the inequality-growth nexus empirical literature. That is the endogenous fertility channel.

The endogenous fertility channel has been put forward as one explanation to reveal the impacts of income inequality on subsequent economic growth (Galor and Zang, 1997; Morand, 1999; Kremer and Chen, 2002; de la Droix and Doepke, 2003). Assuming income is positively associated to one's educational level, families with higher income level (or higher educational background) will normally prefer less children and invest more on each child because the opportunity cost of child rearing is too high for them. As time goes by, the children who are invested more from the affluent households are more likely to become skilled labour and to earn much more, then they will choose less children due to the same reason, the high opportunity cost of taking care of children. On the other hand, poor families will choose more children and with fixed income, they can only invest little per child. A vicious circle can be generated when the poor children enter the labour market as unskilled workers and earn tiny salaries. Then again, with various reason apart from low opportunity cost, these adults from the poor families will choose more children who will be unskilled labour in years later.² In an unequal economy, at the macro

¹ They are the political economy channel, the credit market imperfection channel, and the socio-political instability channel.

² Apart from lower opportunity cost of rearing children, for the poor, choosing more children can also be motivated by insufficient old-age-support (Khoo and Dennis, 1999; Morand, 1998), low education return (Dahan and Tsiddon, 1998), and capital market imperfection (Galor and Zang, 1997).

level, the aggregate level of human capital will be diluted due to the increasing proportion of unskilled labour, therefore impeding the economic growth. Empirically, Perotti (1996) and Kremer & Chen (2002) find that more inequality results in higher fertility rate, no matter measured by net fertility rate in Perotti (1996) or by differential fertility in the latter research. The hypothesis that fertility (or differential fertility) is harmful to subsequent economic growth is also empirically supported by Perotti (1996) and de la Croix & Doepke (2003). However, due to lack of the inter-generational data that includes detailed information of educational background and of income for both parents and children, the related empirical analysis at the micro level is still blank.

To address this unsolved puzzle to the literature in this line, this chapter provides an indirect way to examine the endogenous fertility channel via an evaluation of the One Child Policy. From the previous discussion, what enlarges income inequality in the endogenous fertility channel are the increasing unskilled population and low human capital investment for each child in extended families. The implementation of One Child Policy was exactly to curb the faster population growth rate and improve the ‘quality’ of the next generation. In other words, if the One Child Policy had successfully interfered the fertility and education participation, then the endogenous fertility channel could also explain the effect of income inequality on economic growth in China.

The evaluation of the One Child Policy in this chapter involves a main research question: has the One Child Policy worked in lowering fertility and in increasing the human capital for the next generation? Although the related empirical literature on the examination of endogenous fertility channel is rare, there are some research investigate the casual effects of OCP on fertility and education, respectively. Regarding the effects of the One Child Policy on fertility, the existing literature show different views. One group of research (see Poston & Gu, 1987; Ahn, 1994; McElroy & Yang, 2000; Zhang *et al.*, 2005) proclaim that the OCP has successfully interfered the fast population growth in the 1980s, while another strand of studies argue that the drop of fertility is attributed to the socioeconomic development (see Cai, 2010) or the birth control campaign years before the implementation of the One Child Policy (see Wang *et al.*, 2017; and Whyte *et al.*, 2015).

There are also different opinions with respect to the impacts of the One Child Policy on human capital. For example, by using the Chinese Child Twins Survey data, Rosenzweig and Zhang (2009) conclude that the fertility reduction caused by the One Child Policy had moderate positive impacts on children's schooling attainment at various level. This view is shared by a recent paper of Li & Zhang (2017). However, Liu (2014) cannot find the significant effects of the One Child Policy on education attainment, but he finds a quantity-quality trade-off in children's height.

To answer the research question of this chapter, I particularly generate a retrospective data to recover the birth history for each woman in the sample, which has not been done in any of the existing literature. Compared to previous studies, the superiority of this practice is to provide convenience in reflecting the entire fertility histories of each woman in the sample, which allows one to explore the time-dimension variations and improves the accuracy in identifying the treatment group within the difference-in-differences framework. With the information of children's and mothers' age, and the year of survey, this chapter can further dig into the information of how many children does this woman have, and does this woman give birth to a new child, in a particular year.³ In addition, retrospectively data generation allows pooling more survey data in different waves and therefore increasing the sample size significantly, which is helpful to observe the birth behaviour by different cohort groups. To the best of my knowledge, this chapter is the first study to investigate the treatment effect of the OCP with the retrospective data. In sum, this chapter contributes to the empirically examine the endogenous fertility channel with the natural experiment of One Child Policy. Furthermore, with the retrospective panel data, this chapter hopes to provide a more accurate evaluation of the OCP on the fertility reduction and human capital improvement.

³ For example, for the survey question of how many children do you have, previous literature focus on the information that a woman has two children by the survey year of 1988. However, in this chapter, with the extra information of children's and mothers' age, the retrospective data will offer the information that a woman had two children by the year of 1988. The first child was born in 1975 (before the One Child Policy) and the second one was born in 1980 (after the One Child Policy).

The remainder of this chapter is organized as follows. The second section provides a brief review of the One Child Policy. The following section describes the empirical strategy of difference-in-differences. Section 5.4 and 5.5 provide empirical evidence for the treatment effects of the One Child Policy on fertility and on education participation, respectively. The last part concludes.

5.2. One Child Policy (OCP): A Historical Review

Since the establishment of China in 1949, the population has been increasing dramatically under Mao Zedong's influence.⁴ Before late 1960s, the Chinese government encouraged families to have as many children as possible because Mao believed that population growth could promote China's development. However, high population did not convert to high productivity but economic hardship and collapsing environment (Sudbeck, 2012). Beginning in 1970s, China started to curb its rapid population growth by launching a path of population birth control. Before the official implementation of OCP, Chinese central government initially put forward the concept of family planning with the campaign slogan 'Later (marriage at later ages), Longer (longer the gaps between giving births), and Fewer (fewer the number of children)' in early 1970s (McElroy & Yang, 2000).⁵ At this stage, the birth control was relatively mild as most of them were mainly conducted via persuasions and propagandas. Nonetheless, after the death of Mao and the rise of Deng Xiaoping in the late 1970s, stronger actions were taken to prevent population from overgrowing.⁶ In 1979, Chinese government officially introduced its most controversial and unprecedented birth control policies to the whole nation, which is known as the OCP.

Apart from controlling for the speedy population growth, another important purpose of the OCP is to improve the overall human capital accumulation in China. The official slogan of the OCP, '*you sheng you yu*', delivered the message that giving

⁴ Mao Zedong was the founder father of the People's Republic of China, who is also known as Chairman Mao.

⁵ Explicitly, man from rural area were encouraged to get married later than age 25 while rural women should get married after her 23. This standard of marriage age was even higher for urban residents. In addition, a couple was encouraged to have no more than 2 children and the intervals of giving births should ideally be over 3 years (William, 2014).

⁶ Deng Xiaoping was a paramount leader of the People's Republic of China since Mao Zedong's death.

less birth would lead to better care and education for each child (Peng, 1996). The underlying rationale of this slogan is partly consistent with the famous quantity-quality (Q-Q) model proposed by Becker & Lewis (1973) and Becker & Tomes (1976). The Q-Q model argues that fewer children or smaller family size is preferred for the women whose salaries increase because of the rise of opportunity cost of childrearing. With an assumption that limited resources will be allocated equally to each child, lowering the number of children will lead to higher average quality of children. Although it is controversial, China's central government implemented the OCP to restrict the quantity of children in hope of increasing the 'quality' of the next generation.

Under the OCP, the number of children born after 1979 for each married couple should be strictly restricted to one in hope of reducing the expected population growth. Although there were variations in enforcement among local authorities from different region, the overall implementations of OCP at national level were following a 'carrot and stick' mode. For any 'out-of-plan births', households should be penalized by a heavy fine (which is called a 'social compensation fee') and certain social welfare deprivations. Instead of being punished by violating the OCP, local governments encouraged married women to sign a One-Child Certificate. This certificate is an incentive contract that guarantees certain benefits including fiscal reward and other welfare entitlements. It is worth to note that if the couples violate the OCP after signing the One-Child Certificate, the penalties would be even heavier compared to the cases without signing the pledge (Sudbeck, 2012; Banister, 1987). Fulfilling the OCP is not only important for the households, but also for the local chief cadres of the Communist Party as well. It is local governments responsibility to implement the OCP and to keep the births not exceeding the official permits in their jurisdictions. Otherwise, the officers from the local governments may be demoted according to the Rule of One Vote Vetoes, losing all income and benefits that are associated with government positions (Yang, 2007; Hardee-Cleaveland & Banister, 1988; Short & Zhai, 1998).⁷

⁷ Under the Rule of One Vote Vetoes, the officers who violate the OCP will lost the opportunity to be promoted disregarding his/her past contribution, (great) performance, or future potentials.

Although local governments comply the general the OCP, they show great heterogeneities across regions. Especially, the penalties for out-of-plan birth are significantly heavier for urban residents than their rural counterparts. The punishments for violations of OCP in urban areas are multi-dimensional. Apart from the salary related fine to the above-quota births for urban couples, the urban violators who worked in state-owned companies or organizations might face permanent denial for future job promotion or instant demotion. In particular, urban women may not entitle maternal leave for multiple births. With respect to the above-quota children, they were not permitted to attend the public schools, which were substantially subsidised by local government (Short and Zhai, 1998; Banister, 1997). However, for the rural residents, these related penalties are less deterring. Firstly, in 1980s, the number of rural people who worked for state-owned companies was tiny. Also, majority of rural women were housewives. In this case, the job-related penalties such as salary cut and loss right from maternal leave did not affect rural residents much. Secondly, the public schools were poorly funded in rural areas, which was not only affecting the above-quota children but also for the permitted ones. Third, although cash penalties were the main method for fining violation of OCP in rural China, it was still ineffective because many rural households were too poor to pay the fines (Li *et al.* 2005). Given the difficulties of the OCP implementation in rural areas, for certain rural areas and in certain years, the second birth was allowed for Han women whose first child was a girl (Hardee-Cleaveland & Banister, 1988; Qian, 1997).⁸

Despite the variations of the OCP implementation in local governments, there were some general exceptions that allowed couples to have more than one child. Specifically, the central government imposed tighter birth controls to individuals of Han ethnicity, who constitute more than 90% of China's total population, compared to that of their ethnical minorities counterparts, who were permitted to have more than one child (Hardee-Cleaveland & Banister, 1988; Peng, 1996; Qian 1997).⁹ Although supplementary policies that aimed at restricting fertility rate for ethnical

⁸ There are still enormous differences across rural areas as well regarding the amount of cash fine or girl-exception policy (Li, 1995; Short and Zhai 1998).

⁹ In general, couples from minor ethnical groups were allowed to have up to two children. However, there were still some exceptions such as minority women in Xinjiang province and in rural Tibet province (Li, Zhang, & Zhu, 2005).

minority groups with over 10 million population at the end of 1980s, the implementations were less strict. Up to 1990, two (out of fifty-six) ethnical minority groups, namely Zhuang and Man, were subject to the OCP, as they passed through the population policy threshold (Li *et al.* 2005). This exemption from the OCP for ethnical minorities provides a unique natural experiment set up for researchers to investigate the policy evaluation of the OCP, treating ethnical minority couples as control group and Han women as experimental group.¹⁰

To sum up, the OCP was enforced for the purposes of controlling fast population growth and improving quality of the next generation. Taking the unique advantage of ethnical differentiation of the OCP implementation, the policy evaluation could be conducted under a natural experiment context, treating Han Chinese as treatment group and other ethnical minorities as control group. The following section will explicitly introduce the empirical strategy to investigate if the OCP exerted significant impacts on slowing population growth and on enhancing children's education.

5.3 Empirical Strategy

As discussed in the last section, the OCP was designed for slowing down the fast population growth and improve the human capital accumulation particularly for the next generation. In an econometric setting, the policy evaluation of the OCP could be divided into two stages: the first stage of this chapter is to assess the treatment effects of the OCP on birth control; the second stage is to examine the impacts of the OCP on education for teenagers. Essentially, due to the ethnical differentiation of the OCP implementation, the effects of the OCP could be assessed under a difference-in-differences (DD) framework. DD is an identification strategy to investigate treatment effects comparing the before- and after- treatment in the observable outcomes of experimental/treatment groups and control groups, which has been widely used in policy evaluation research.

¹⁰ Other general exempt cases from the OCP include the situation when the first child cannot join the labour force due to non-hereditary disability; when the remarriage couples only have one child before their second marriage; when the couples are the only child from their families; when more than one child is born within one pregnancy; and when there is an early death of the only child to a couple (Liu, Larsen, & Wyshak, 2005).

How could DD be applied to evaluate the effects of the OCP? As introduced in the last section, the OCP was officially enforced in 1979, specially to Han Chinese women, which constituted the biggest natural experiment in human history. In the experiment setting, treatments are the restrictions on the number of children per household for Han Chinese (treatment group), leaving the ethnic minorities unchanged (control group). In an econometric setting, the research focus is on examining the impacts of the treatment (D_{it}) on outcome variables (Y_{it}), as in

$$Y_{it} = \lambda_t + \alpha_i + \rho D_{it} + \mathbf{X}'_{it}\boldsymbol{\beta} + u_{it}, t = 1, \dots, T \quad (5.1)$$

where α_i are individual time-invariant fixed effects; λ_t are time specific fixed effects that will not change across individual; D_{it} is a dummy variable. It equals one when the individual is in the treatment group (Han Chinese) and post-treatment (post-1979), and equals zero otherwise.¹¹ \mathbf{X}_{it} are time-varying controlling variables. Y_{it} is an outcome variable that should be a measure of fertility in the first stage, and that should be a proxy of education situation in the second stage. u_{it} is an error term.

The coefficient of interest is ρ , the DD estimator. Under the assumption that the changes in Y_{it} for Han and non-Han would have been identical in the absence of the OCP, ρ captures the casual effects of the OCP on outcome variable (measures of fertility or children's education).¹² This assumption will be testified in the robustness check subsection. In the first stage, it is expected that ρ should be significantly negative, suggesting that the OCP has curbed the speedy population growth of Han Chinese compared to that of their ethnical counterparts. In the second stage, when I examine the treatment effects of the OCP on children's education, the sign of ρ is expected to be positive. If both expectations are supported by empirical results, it can be concluded that the endogenous fertility channel was predominant in China.

¹¹ Empirically, D_{it} is the interaction term Han \times Post1979. It equals to 1 only when the treatment group (Han=1) receive treatment (Post1979=1).

¹² This is also known as parallel trend assumption.

The key assumption of DD strategy is the parallel assumption. It suggests that both control and treatment group should share the same trend on the change of outcome variable when the treatment is absent. If the parallel assumption is violated, then the estimated treatment effect may not merely capture the casual impacts of the treatment on the outcome variable. In this chapter, the pre-trend tests are conducted for both stages as robustness checks in the Appendix 5A.

5.4 First Stage Estimation: the OCP on Fertility

Data

The data used in the current chapter is mainly derived from CHIP, the same dataset that has been used in the last chapter. It was initiated by researchers from Beijing Normal University and Australian National University, and is supported by the China National Bureau of Statistics (NBS), and the Institute for the Study of Labour (IZA). The surveys were implemented by NBS through a series of face-to-face questionnaire-based interviews, covering both rural and urban areas in China in 1988, 1995, 2002, 2007, 2008, 2013. CHIP collects data at both individual and household level, including sources of incomes and expenditures, employment status, education level, fertility, and economic characteristics.

To investigate the effects of the OCP in birth control, the outcome variable Y_{it} should be a measure of fertility. Ideally, it should be the variable that reflects the number of children that a woman has given birth to in her entire life history. Unfortunately, CHIP data does not provide this information except for CHIP 2007 and CHIP 2008.¹³ Instead, for the first stage the OCP evaluation, the outcome variable, Y_{it} , is a binary variable that equals to one when a woman ‘ i ’ gives birth to a child in year ‘ t ’, otherwise zero. Then the regression estimates the impacts of the OCP on the probability for a woman to give birth to a child. It is worth to note that the woman ‘ i ’ is referred to the head of household or its spouse while the child is referred to the family member who is the biological child of the head of household. For example, if CHIP data shows that the respondents from a household include head of household, spouse, parents of the household-head, and three children, the

¹³ In CHIP 2007 and CHIP 2008 questionnaires, women were asked that ‘how many children do you have’. But this question did not exist in other waves of CHIP questionnaire.

number of children in this case should be counted as three.¹⁴ By combining all waves of CHIP data (except for CHIP2008), there are 77180 defined women in whole sample.¹⁵

One potential concern on this measure is that the true number children were born will be underreported because CHIP data only report the number of children being at home at the time of interview, ignoring the ones who move away from home. Going back to the previous example, it is likely that some children who were studying or working in other cities in China would have been ignored by CHIP data.¹⁶ One way to deal with the underreporting issue of this kind is to restrict the sample by women's age. The underlying rationale is that the younger women are not likely to have mature children who are old enough to leave home for study or work in other cities. In other words, the children that are recorded in CHIP data will close to the true number of children that the mother has given birth to. Hence, I restrict the sample to women whose age were between 15 and 45 in for all wave of CHIP survey. In the whole sample, the data reports that the mean age of the women who gave their first birth is 25.3 years old. In addition, children who should complete their primary and secondary education will not leave their home city until their 18 years old.¹⁷ These two facts contribute to the selection of upper bound as 45 years old of women. The estimation results of younger mothers (15-38, and 15-30) for the purpose of robustness check are also provided in the following empirical evidence subsection.

¹⁴ Strictly speaking, the pair between the head of household/spouse and their parents could also be counted as a parent-child relationship. However, the CHIP data does not provide enough information from the mother of the household head/spouse, particularly on the birth history. Therefore, I only consider parent-child relationship between the head of household/spouse and their children, but not the head of household/spouse and their parents.

¹⁵ CHIP2007 and CHIP2008 traced the same household in these two years, consisting a panel data. To avoid the double counting issue, I drop the 2008 wave.

¹⁶ Residential registration system (also known as Hukou system) has less effects on the citizens who attend tertiary education and who have a job in other city. In other words, children are more likely study in local schools before receiving their tertiary education or pursuing their career elsewhere.

¹⁷ It is calculated by author based on the information that the compulsory school age in China is 6 years old, and that the normal primary and secondary education in China last 12 years in total. Due to the Hukou system, student who wants to attend a public funded school cannot go to the school that are not in the area where they registered.

With these restrictions, I obtain a subsample of 41592 Chinese women. The related summary of statistics is shown in the Table 5-1. Overall, in the age-restricted sample, the mean values of age are close for both Han and Non-Han women. But there are more rural residents (73.5%) in Non-Han group, while the same index for Han women is only 55.4%. In addition, the proportion of ethnical minority Chinses (Non-Han) is tiny, taking account for only 6.3% of the sample. It is worth to note that the mean number of children for Non-Han Chinese women (2.024) is higher than the Han Women (1.640). However, it is not sure yet that if it is the result of the OCP.

Table 5-1. Sample Summary Statistics for Women Age 15-45

Variable	Overall	Han	Non-Han
Age	36.784 (5.727)	36.840 (5.694)	36.109 (5.888)
Rural	0.565 (0.496)	0.554 (0.497)	0.735 (0.441)
No. of Children	1.665 (1.007)	1.640 (0.992)	2.024 (1.139)
No. of observation	41592	39144	2448

Note: Rural is a dummy variable that equals to one for rural residents, otherwise zero.

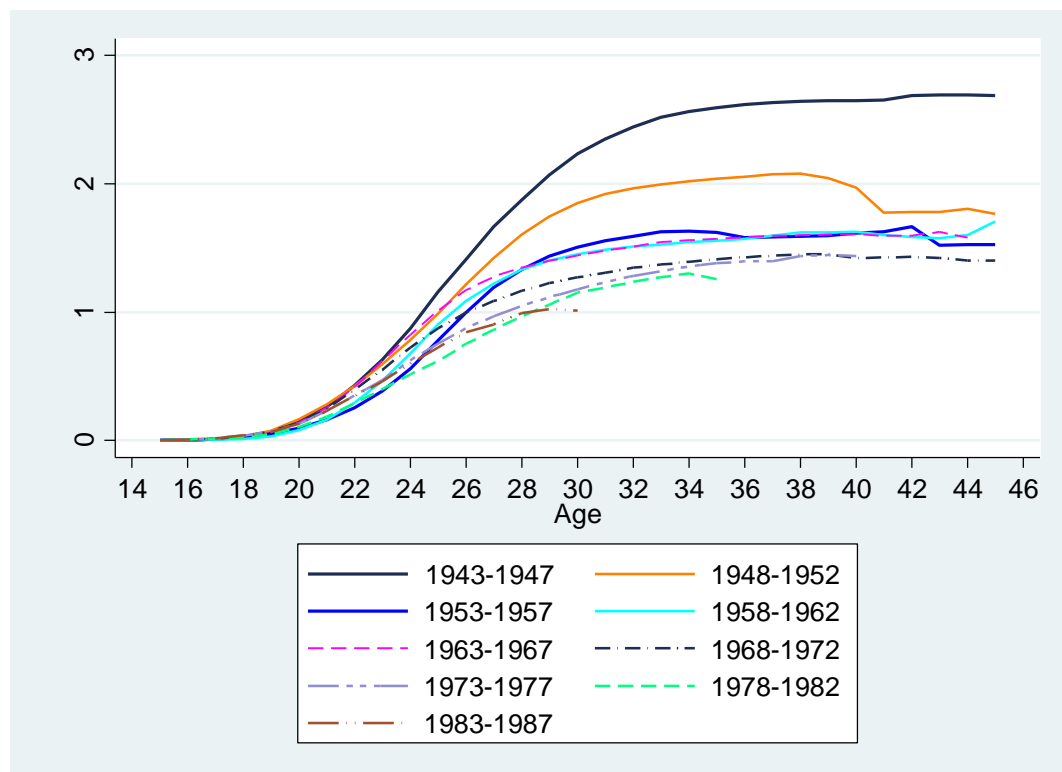
To assess the OCP effects on fertility, I regenerate the birth history for the age-restricted sample by employing their children's information. Specifically, with the age information of their children, it can be inferred that if a woman gives birth to a baby in a specific year. For example, CHIP1988 data shows that a 35-year-old woman has a 10 years old child. In other words, this woman gave birth to her first child when she was 25 in 1978. Following the same logic, the new panel data covers 939709 observations from 1958 to 2013, with the cohort group from 1943 to 1998.

Figure 5-1 describes the number of child per household at different age of women who are head of household or its spouse. Each (solid/dash) line represents a group of five birth cohorts of these women since 1943.¹⁸ The horizontal axis is the age for the women in the sample while the vertical axis is the averaged number of child per household for each (grouped) birth cohort. At the first glance, each line in the figure

¹⁸ The cohorts after 1987 are dropped due to the sparse observations. The related information is available upon request.

5-1 can be divided into two phases in general. The J-curve or the steep phase implies the period when the probability of giving birth to a new baby is increasing dramatically, which normally happens between 20 and 30 for each birth cohort group. The second phase is shown as the flat part of each line, which suggests that the growth rate of probability of having a new child is decreasing and the average of number of children converges to a certain level. In addition, the flat phase can be explained by the fact that woman has finished her childbearing years when getting older.

Figure 5-1. Number of Child per Household by Age in Various Birth Cohort



Note: The line plots the average number of child per household at different ages of children's mother. Every (solid/dash) line represents a group of five birth cohorts of children's mother.

The first message delivered by the figure 5-1 is that the number of child per household is decreasing cohort by cohort. The oldest birth cohort group of 1943-1947 have more than two children at their 30 while the number reduces to just above one at the same age for the youngest cohort groups (1983-1987). Particularly, it is worth to note that the decrease in number of new born children is not happening steadily until two significant drops for cohort group 1948-1952 and for 1953-1957. For these two cohort groups, they were 21-30, the peak time for giving

birth to babies, when the OCP was officially introduced. In this sense, the significant drops on the number of child per household for the cohort of 1948-1957 strongly indicate that the OCP has impacts on fertility reduction. In this sense, the significant drops on the number of child per household for the cohort of 1948-1957 strongly indicate that the OCP has impacts on fertility reduction. This will be further investigated with DD estimator in the empirical result subsection.

In addition, the peak time for women to give birth to a child is narrowing down cohort by cohort, which is suggested by the longer flat part and shorter steep component from the older cohorts to the younger ones. For the oldest cohort group (1943-1947), the average number of child per household is increasing dramatically before plateauing at their 32. However, the same plateaus appear earlier and earlier for younger generations. These evidence implies that women will finish their childbearing age earlier with less children in general, which again indicates that the OCP has effectively intervened the overpopulation.

Apart from the standard DD regressors (treatment group, post treatment, and its interaction term), other explanatory variables include women's age, age squared, and the number of child that the woman has in time ' t '. It is expected that the coefficients on the age and age squared are significantly positive and negative, respectively, indicating that the probability of having a child is increasing at a decreasing rate as they become older. This prediction has visually shown in the figure 5-1 as well: the slope of the line is decreasing as age goes up. With respect to the quantity of child, I categorize this variable into three groups, namely, none, one, and more than one. Under the OCP context, a Han Chinese couple should not have new baby if they have child(ren) already before 1979. In this case, it is expected that the probability of having a new child will be higher when the couple does not have one, the probability which will decrease otherwise due to the OCP enforcement.

First Stage Empirical Results

The first stage empirical results have been summarized in the table 5-2. I initially examine the regression 5.1 without other controlling variables as baseline regression, which is shown in the column (1) of table 5-2. The coefficient (ρ) on the

interaction term ‘Han \times Post1979’ is the treatment effect of the OCP on fertility. It has the expected negative sign and statistically significant at 5% significant level, suggesting that the probability of having a new baby after the OCP implementation will be lower by 1 percentage point, compared to their ethnic minority counterparts. Column (2) shows the estimation result with other controls such as age, age-squared, and dummies for number of children. Similar to the baseline model, the magnitude of estimated ρ is slightly higher (2.8 percentage points) with the expected negative sign. Compared to the sample mean probability of having a child (0.071), the OCP treatment effects on fertility is large, dropping by almost 39.44%. With regard to other explanatory variables, the coefficients on age and age-squared are strongly significant with the expected signs, indicating that the probability of having a new child for Chinese women increases at a declining rate as age goes up. Furthermore, as expected, the empirical results in column 2 reveals that the probability of having a new child will be 18.5 percentage points higher for the couple that do not have child compared to the ones who have one already. In addition, the probability of giving birth to a new baby is 37 percentage points lower if they have more than one child, compared to the reference group (no child).

One might argue that the upper bound of age 45 is still too old as some children will move away from home. If it is the case, then the number of children that have been used in this chapter so far still undermeasure the true value. The last column of the table 5-2 is the subsample by dropping the women who are over 38 years old.¹⁹ As shown in the figure 5.1, the number of child per household for each cohort group should converge to certain level, suggesting that the women in this cohort will not have any new child after certain age. However, there are two significant drops for cohort group 1948-1952 and 1953-1957. To make the number of child that are being interviewed by CHIP survey conductor close to the true number of child that are being born, I keep all the data that are less problematic, that is, before age 39. Column (3) in table 5-2 shows that the magnitude of the estimated treatment effect of the OCP is exact same as the one obtained by using whole sample.

¹⁹ I also test the subsample with the women who are 15-35 and 15-30, respectively. The coefficients on the Han \times Post1979 for the former case is unchanged and statistically significant at 1%. The coefficients on the Han \times Post1979 for the 15-30 subsample is twice as large as the previous results, and significant at 1% level.

Considering that the sample mean for the younger cohorts are slightly higher (0.079), the treatment effects is relatively weaker when the older cohorts are dropped out, accounting for about 35.44% reduction in probability of having a new child. Regarding the coefficients on other variables, they are slightly larger in magnitude.

Table 5-2. Estimation Results for Treatment Effects of the OCP on Fertility

Variables	(1)	(2)	(3)
Han × Post1979	-0.010** (0.005)	-0.028*** (0.005)	-0.028*** (0.008)
Age		0.077*** (0.000)	0.096*** (0.001)
Age ²		-0.001*** (0.000)	-0.002*** (0.000)
1 Child		-0.185*** (0.001)	-0.213*** (0.001)
>1 Child		-0.370*** (0.001)	-0.412*** (0.002)
Constant	-0.024*** (0.002)	-0.961*** (0.006)	-1.164*** (0.008)
Person fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
No. observation	939709	939709	425984
Sample	Whole	Whole	Age<39
Sample Mean	0.071	0.071	0.079
R ²	0.008	0.043	0.051

Note: The reported standard errors in parenthesis are robust to cross-sectional heteroskedasticity and residual serial correlation. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level. The number of children is a categorical variable where 0 is no child, 1 is only one child, other cases should be 2. The reference group is the case with no child.

Heterogeneous Treatment Effects of the OCP on Fertility

Empirical results in the table 5-2 verify the hypothesis that the OCP had significant impacts on lowering the probability of having a new child of Han Chinese women relative to their ethnical minority counterparts. To examine if the results are robust across women with different time-invariant characteristics, I test the same model 5.1 with FE estimator for different subsamples. The related estimation results are provided in Table 5-3.

Apart from the purpose of robustness check, it is also interesting to see if the OCP has different effects on the women with different educational background. On the

one hand, social scientists have long observed that fertility drops with increasing women's education attainment as suggested by Becker & Lewis (1973) and Becker & Tomes (1976). If it is the case, then it should be expected that the OCP has less impacts on Han Chinese with higher educational background. On the other hand, Li *et al.* (2005) argue that better-educated Han Chinese women are normally associated with better jobs and higher salaries. Since the penalties for above-quota birth may involve the fines that are proportionally to one's salary, and demotion from the current position (Short and Zhai, 1998, Banister, 1997), the more educated women are more willing to comply with the OCP to avoid higher violation cost. If it is the case, then the magnitude of estimated treatment effects should be larger for better-educated women.

In the first three columns in the table 5-3, the whole sample is divided by women's educational background. Specifically, I categorize women's educational background into three groups, namely, less educated, medium educated, and educated. Less educated is the case when a women's highest education qualification is primary school or lower. Educated is the case when a women's highest education qualification is undergraduate degree or above. Other cases should be counted as medium educated.

At the first glance of the table 5-3, the sample mean of the first three columns supports the hypothesis that women with higher education attainment are less likely to have children. The probability of having a child for the less educated women (0.102) are twice as large as the one for the educated women (0.048). Correspondently, the estimation of the treatment effects of the OCP on fertility is the strongest for the less educated women (-3.7 percentage points less than the Non-Han Chinese less educated women), and is the weakest for the educated women (-0.5 percentage points), accounting for about 36.27% and 10.42% reductions for the less educated and the most educated women, respectively. These evidence suggests that although the OCP has negative impacts on the probability of having a new child in general, the elite women are less effected. For the women who are located at the medium education category, the estimated ρ is close to the one obtained by the whole sample, suggesting that the probability of having a new baby for Han Chinese is 2.4 percentage points lower relative to the ethnical minorities.

Empirical results for other controls are also interesting. From the least-educated subsample to the most-educated one (column 1 to 3 in the table 5-3), the empirical results show a pattern that the age affects the probability of having a child the most to women with lower education background. But such age effects will be mitigated with the increase of women's education attainments. Furthermore, compared to the women who have no child, the most-educated group who have already have one child shows strong dislike to have a new baby (22.5 percentage points lower in probability shown in column 3), but such unwillingness is absent in for the least-educated subsample (only 9.1 percentage points lower in probability shown in column 1).

In summary, although the magnitude of the OCP treatment effects on Han women vary with different educational level, they consistently show that the probability of having a new child for Han Chinese women is lower than the one for the Non-Han Chinese women. In addition, the estimation results from the medium educated group (column 2 in the table 5-3), which accounts for more than 70% of the total observations, are close to the ones obtained by the whole sample (column 2 in the table 5-2). Therefore, it can be concluded that the treatment effects of the OCP is robust.

Next, I divide the whole sample into two groups, urban and rural. As discussed in the section 5.2, the OCP implementation shows great heterogeneities across regions especially for the violation penalty. In general, it is expected that the OCP treatment effects affect the urban residents more simply because the penalties for above-quota child births are more severe for couples form urban areas. As pointed out by Li and Zhang (2004), the OCP enforcement in rural areas are not as efficient as in urban areas because many rural households are too poor to be fined for out-of-plan child. I examine the regression 5.1 with FE estimator to women from rural and urban areas, respectively, as shown in column 4 and 5 of table 5-3.

Table 5-3. Treatment Effects of the OCP on Fertility for Subsamples

Variables	(1)	(2)	(3)	(4)	(5)
Han ×	-0.037***	-0.024***	-0.005***	-0.026***	-0.009*
Post1979	(0.010)	(0.005)	(0.012)	(0.006)	(0.005)
Age	0.095***	0.079***	0.052***	0.03***	0.058***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Age ²	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1 Child	-0.091***	-0.199***	-0.225***	-0.162***	-0.224***
	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)
>1 Child	-0.360***	-0.381***	-0.367***	-0.390***	-0.378***
	(0.004)	(0.001)	(0.012)	(0.006)	(0.002)
constant	-1.129***	-0.983***	-0.697***	-1.140***	-0.763***
	(0.147)	(0.008)	(0.014)	(0.008)	(0.008)
Person fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
No. obs.	135420	665226	136577	536743	402966
Sample Mean	0.102	0.070	0.048	0.087	0.051
Subsample	Less	Medium	Educated	Rural	Urban
	Educated	Educated			
R ²	0.067	0.049	0.062	0.060	0.061

Note: The reported standard errors in parenthesis are robust to cross-sectional heteroskedasticity and residual serial correlation. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level. The number of children is a categorical variable where 0 is no child, 1 is only one child, other cases should be 2. The reference group is the case with no child.

At the first glance, although the sample mean of probability of having a child is relatively smaller in urban areas (0.051), the OCP impacts for the urban subsample (-0.9 percentage points) is much weaker, which is only at 10% significant level. This suggests that the probability of having a new child for urban Han Chinese women just slightly 0.9 percentage point lower compared to the Non-Han women accounting for about 17.65% reduction compared to the sample mean. In addition, the same probability is 2.6 percentage points lower in rural areas, which is close to the estimation of the whole sample (2.8 percentage points, as shown in column 4, table 5-2). Compared to the sample mean, this could be translated as about 30% reduction in probability. One possible explanation is that urban residents are less likely to have more children even before the OCP. As a result, the women from urban areas are less affected although the OCP enforcement are relatively stricter.

To sum up, the first stage of this chapter is to assess the OCP effects on fertility by treating Han Chinese women as treatment group and Non-Han Chinese women as control group. With the DD technique, I find that the probability of giving birth to a new child for Han Chinese women is 2.8 percentage points lower compared to the Non-Han women. After series of test of the OCP treatment effects on women with other time-invariant characteristics, it can be confirmed that the OCP implementation exerted negative impacts on fertility. However, such effects were relatively weaker for women with higher education background (undergraduate degree or above), and for women from urban areas.

5.5 Second Stage Estimation: the OCP Effects on Child's Education

Data

To investigate the OCP treatment effects on child's education, I continue to draw on the CHIP data for the waves in 1988, 1995, 2002, 2007, and 2013. The outcome variable Y_{it} in regression 5.1 in this stage is a binary variable that equals to one when a child is attending school that is higher than junior secondary school by the time of survey and equals to zero otherwise. This is indicated by the survey question of 'Are you still attending school?' for the children who are between 14 and 22 years old.

In China, a typical student normally starts his/her primary stage education no later than 6 years old, which takes 6 years to complete in general cases.²⁰ When it comes to the secondary stage, both junior and senior secondary education take 3 years to finish, respectively. In general cases, it should take four years for one to complete the tertiary education in China.²¹ The primary and junior secondary school education composes the nine-year compulsory education. As a result, a child who receives the compulsory education from 6 years old should decide whether attend senior secondary schools (also known as high schools) at the age of 15 and would possibly finish his/her high school at the age of 18, and tertiary education at the age of 22. Considering the possibility that some children will start slightly earlier than 6

²⁰ Under certain exceptional circumstances, school age children can attend primary school education no later than 7 years old.

²¹ It could be more than four years depending on a specific undergraduate program. It is worth to note that, unlike the UK education system, there is no placement program in China for the higher education yet.

years old, the sample also includes all children who ages between 14 and 22 across all waves of CHIP.

Then the regression 5.1 estimates the treatment effects of the OCP on the probability of attending school for school-age children. Particularly, the children in the second stage estimation is defined as the one whose relationship to the head of household is ‘children’ in the CHIP survey for two reasons. Firstly, the purpose of the OCP is to improve the ‘quality’ of the next generation, which makes the second stage estimation focusing on children. Secondly, empirically speaking, the probability of attending further education after junior secondary education might also be influenced by parents’ educational background. However, this information is only available for the observation who is ‘children’ to the head of household. As a result, the whole sample includes 38147 children who were born during the periods 1966-74, 1973-1981, 1980-88, 1985-93, and 1991-1999.

The descriptive statistics of the sample for the second stage estimation are summarized in the table 5-4. From the first glance, majority of the observations are rural residents (75.2%) and more than 90% are Han Chinese. With regard to the mean of number of siblings, the one for ethnical minority (1.821) is much higher than the one for Han Chinese (1.330), which could be explained by the intervention of the OCP on fertility. Regarding the education background for the parents, Han parents have relatively better education compare to Non-Han parents. Furthermore, fathers have relatively higher education background relative to mothers in general. Student is a dummy variable that equals to one when the child is attending school during the survey, otherwise zero. It shows that ratio of attending school for the Han children (0.455) is slightly higher than their ethnical minority, which could support the hypothesis that the OCP improves the child’s education level.

Table 5-4. Sample Summary Statistics for Children Age 14-22

Variable	Overall	Han	Non-Han
Age	18.125 (2.482)	18.141 (2.480)	17.929 (2.500)
Rural	0.752 (0.432)	0.743 (0.437)	0.850 (0.357)
No. of Siblings	1.367 (1.191)	1.330 (1.165)	1.821 (1.397)
Student	0.452 (0.507)	0.455 (0.506)	0.417 (0.518)
Mum Edu.	3.252 (1.497)	3.283 (1.497)	2.865 (1.442)
Dad Edu.	3.948 (1.273)	3.984 (1.264)	3.501 (1.303)
No. of observation	38417	35536	2881

Note: ‘Student’ is a dummy variable that equals to one when the child is attending school during the survey, otherwise zero. Mum and Dad Edu. are categorical variables including 7 categories. 2, 3, 4 mean the highest education qualification is primary school, middle school, and high school respectively

In practice, the baseline model includes only Han, Post1979, the interaction term $\text{Han} \times \text{Post1979}$, and time dummies. Under the DD framework, the coefficient of the interaction term should be the treatment effects of the OCP on the probability of attending school for the children between 14-22 years old. Based on the first stage empirical evidence that the OCP effectively lower the fertility rate for the Han women, the coefficient on $\text{Han} \times \text{Post1979}$ is expected to be positive, suggesting that the goal of the OCP of improving children’s quality can be fulfilled.

Apart from the baseline regression, age dummies, number of siblings, and parental education background indicators are also included in extended regressions. If the famous Q-Q model is in place, then the coefficient on the number of siblings should be negative, implying that more children indeed lower the quality of each child. Regarding the parental education background, I re-categorize the original variable into three groups: less educated means that one (either mother or father) has the highest education qualification of primary school or lower; when educated means that they have the highest education qualification of undergraduate degree or above. Other cases should be counted as medium educated. The coefficients on parental education background should be positive. On the one hand, greater education background may lead to higher salary for their parents. In this case, there will be

more resources to be invested on each child, increasing the probability of attending school. On the other hand, educated parents want their children to have better education background for the sake of potential higher salary or successful career.

Second Stage Empirical Results

Table 5-5 summarizes the second stage empirical results. The baseline regression is reported in column (1). The coefficient on the interaction term is 0.048 and significant at 1% level, suggesting that the treatment effect of the OCP increase the probability of attending school for Han children who are between 14-22 years old by 4.8 percentage points. Even when I include other covariates in the model, the coefficients of Han \times Post1979 are still significantly positive and slightly higher (5.6, and 6.1 percentage points, respectively), as shown in the column (2) and (3) in table 5-6. These are strong evidence that the OCP exerted positive impacts on improving the quality of children of next generation. In addition, compared to the sample mean of the probability of education participation (0.439), the OCP treatment effects is moderate, accounting for about 13.5% increase to the mean.

Table 5-5. Estimation Results for Treatment Effects of the OCP on Education Participation

Variables	(1)	(2)	(3)
Han × Post1979	0.048*** (0.002)	0.056*** (0.001)	0.061*** (0.002)
Post1979	0.510*** (0.001)	0.061** (0.012)	0.058** (0.011)
Han	0.031*** (0.000)	0.007 (0.009)	0.008 (0.010)
No. Siblings		-0.052* (0.017)	-0.035* (0.015)
Medium Educated Mum			0.081*** (0.010)
Educated Mum			0.206*** (0.003)
Medium Educated Dad			0.042 (0.019)
Educated Dad			0.290*** (0.012)
Constant	0.094*** (0.001)	0.708*** (0.029)	0.266*** (0.007)
Age dummy	No	Yes	Yes
Year dummy	Yes	Yes	Yes
No. observation	40956	40956	38417
Sample Mean	0.439	0.439	0.452
R^2	0.195	0.402	0.393

Note: Standard errors reported in brackets are clustered for the treatment and ethnicity level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level. The reference groups for the parental education backgrounds are less educated Dad and less educated Mum.

The coefficients on other variables also meet the expectations. The regression results in column (2) show that the coefficient on the number of siblings is negative and significant at 1% level, confirming the Q-Q model. Specifically, the estimation suggests that one more sibling will reduce the probability of attending school by 5.2 percentage points on average. When controlling for the parental education background additionally (column 3), the effects of siblings reduces to 3.5 percentage points and still significant at 10% level. In addition, with the higher education background, the magnitudes of the coefficients are larger. For example, compared to the reference group when a mother's highest education qualification is primary school or lower, the ones who hold at least a middle school certificate will increase their child's probability of attending school by 8.1 percentage points. This increase of probability is even higher (20.6 percentage points) for the mothers who

hold the higher education certificate. It is also worth to note that the education background for parents are equally important as the magnitude of the corresponding coefficients are close.

Heterogeneous Treatment Effects of the OCP on Education

The empirical evidence has clearly support the hypothesis that the treatment effects of the OCP will increase the probability of attending further study for the children who are 14-22 years old. The next question is: do these effects vary across gender, region, or age? Traditional Chinese (especially in rural areas) value male over female, which has deprived the rights of receiving education for the girls. Given the same situation, the family would be more likely to send their son to school, generating the gender gap of education attainment in China. This is supported by my data as shown in the bottom of the table 5-4. The sample mean of the probability of education participation for boys are 4 percentages points higher than the probability for girls (0.440). With the help of the OCP, the probability of attending school for girls is expected to be higher because the number of sibling is decreasing, and the competition with their male siblings is less intense. In other words, the treatment effects of the OCP should be stronger for girls over boys. In addition, as discussed in the first stage, the OCP treatment effects on fertility is much stronger in rural areas. If the OCP indeed has impacts on children's education via the Q-Q theory, then the treatment effects of the OCP on education should be again stronger in rural area. This subsection examines the same model in the second stage estimation for different subsamples, the results which are reported in table 5-6.

Column (1) and (2) report the empirical results for the treatment effects of the OCP on education across gender. The coefficients on $\text{Han} \times \text{Post1979}$ are positive and significant for boys and girl. Specifically, the results show that the probability of attending schools for Han girls will increase by 4.8 percentage points, while the same probability increase for Han boys is 7.2 percentage points, suggesting that the OCP treatment effects are stronger on boys. It violates the prior guess and suggests that the strong gender inequality in China is still persistent even after the OCP implementation. This is also can be checked with the coefficients on the siblings. When the ones for males indicate that the probability of education participation will

be decrease by 2.8 percentage points with one more sibling. However, this coefficient is not significantly different from zero for female. This might suggest that the family size is not a factor to affect the girls' chance of receiving education. Instead, the treatment effect on education for female is relatively lower is only because they are female. Column (3) and (4) show the empirical results for the treatment effects of the OCP on education across region. As expected, although the coefficient on the interaction term is positive, it is no longer significant for the urban residents. This might be the results of small sample for the urban residents. The same coefficients for rural residents is 5.4 percentage points, which is robust to the results obtained from the whole sample (column 3, table 5-5). These empirical evidence across regions again confirms the OCP treatment effects on both fertility and education.

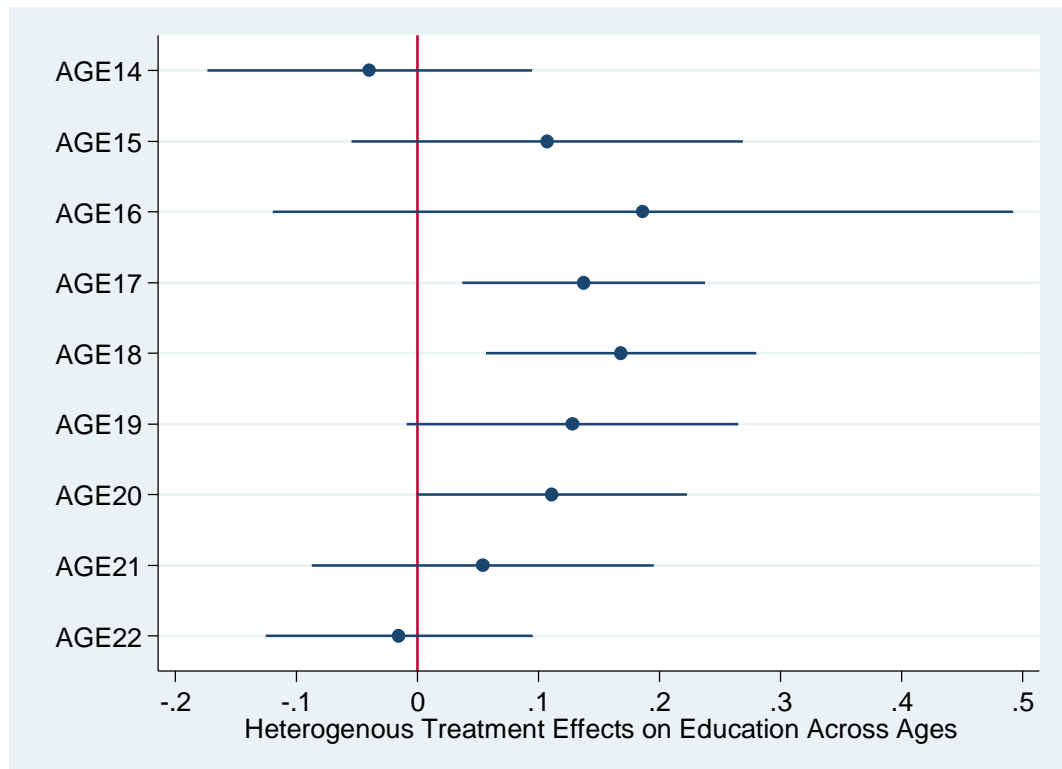
Table 5-6. Treatment Effects of the OCP on Education Participation for Subsamples

Variables	(1)	(2)	(3)	(4)
Han × Post1979	0.072*** (0.002)	0.048*** (0.002)	0.001 (0.011)	0.054*** (0.001)
Post1979	0.035** (0.011)	0.084** (0.026)	0.160 (0.111)	0.050 (0.041)
Han	-0.010 (0.009)	-0.003 (0.013)	0.032*** (0.005)	-0.008 (0.007)
No. Siblings	-0.028* (0.012)	-0.041 (0.020)	-0.018* (0.007)	-0.015 (0.011)
Medium Educated Mum	0.066*** (0.008)	0.097*** (0.014)	0.076*** (0.012)	0.048** (0.010)
Educated Mum	0.174*** (0.017)	0.240*** (0.010)	0.129*** (0.007)	0.166*** (0.021)
Medium Educated Dad	0.047** (0.012)	0.038 (0.027)	0.019 (0.012)	0.039* (0.017)
Educated Dad	0.206*** (0.009)	0.172*** (0.017)	0.087*** (0.010)	0.141*** (0.021)
constant	0.596*** (0.010)	0.572*** (0.020)	0.448*** (0.123)	0.609*** (0.026)
Age dummy	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes
No. observation	19767	18645	9536	28881
Subsample	Male	Female	Urban	Rural
Sample Mean	0.464	0.440	0.662	0.383
R^2	0.396	0.394	0.481	0.400

Note: Standard errors reported in brackets are clustered for the treatment and ethnicity level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level. The reference groups for the parental education backgrounds are less educated Dad and less educated Mum.

The figure 5-2 shows the coefficients on the OCP treatment effects on education participation across ages. At the first glance, the positive policy impacts were significantly stronger for the Han children who are aged 17-20, whose probability of attending school increased around 13 percentage points after the OCP implementation. In China, students who are between 17 to 20 are generally attending final year of high schools, vocational schools, or universities. Therefore, the estimation results indicate that the OCP treatment effects strongly encouraged the students to participate the education, especially for the tertiary education. However, for the ones who are under 17 years old and over 20 years old, the OCP treatment effects were insignificant.

Figure 5-2. Heterogenous Treatment Effects of the OCP on Education Across Ages



Note: The dots depict the coefficients of the treatment effects of the OCP on outcome variables for different ages with 95% confidence intervals.

5.6 Conclusion

Despite the controversy of the OCP implementation, this chapter evaluates its casual effects on fertility reduction and education participation improvement within a difference-in-differences framework. The estimation results suggest that the probability of having a new child for Han Chinese women is lower than their ethnical monitories by about 2.8 percentage points, after the OCP implementation.

Such effect is robust to a series of sensitivity checks. Compared to the sample mean of 7.1 percent, the treatment effect is large on fertility, taking account for almost 40% reduction of the sample mean. However, the influence of the OCP on fertility is much weaker for the educated women and urban residents.

The second stage estimation results of this chapter indicate that the casual effects of the OCP increase the probability of education participation of Han children aged 14-22 by about 6.1 percentage points. Compared to its sample mean of 44%, such effect takes account for about 14% to the mean. It is worth to note that the policy effects on education participation is stronger for boys, suggesting the gender inequality on the chance of receiving education. Again, the OCP has exerted positive impacts on increasing the probability of schooling is much stronger for rural residents. Also, from the OCP treatment effects are specifically stronger for the children between 17-20, who are more likely receiving tertiary education.

Based on these estimation results, the fertility elasticity of education is -0.35, suggesting that 1% change in the probability reduction of having a child will lead to a 0.35% change in probability increment of a child (aged 14-22) to attend school. The empirical evidence in this chapter partly supports the finding in Li *et al.* (2005). They find that the probability of having a second child is 11 percentage points lower for Han Chinese after the birth control policy. However, they also conclude that the treatment effect is much stronger in urban areas, which is not supported in this empirical chapter. With respect to the empirical results from the second stage, this chapter suggests a moderate policy impacts on education participation, which is supportive to the findings in Rosenzweig and Zhang (2009) and in Li *et al.* (2017), even though they are not using the same data set and estimation strategy.

Most importantly, the empirical results from this chapter solve the puzzle that has been left in the Chapter 4, the investigation of the endogenous fertility channel. Although the OCP has been abandoned nationally in 2016, this chapter finds that the OCP has successfully intervened in overpopulation and human capital dilution. These findings confirm that the endogenous fertility channel can explain the negative inequality-growth nexus in China.

Appendix 5A Robustness Check: A Test on Pre-Trend

5A.1 First Stage Robustness Check: A Test on Pre-Trend

The key assumption of DD strategy is the parallel assumption. It suggests that both control and treatment group should share the same trend on the change of outcome variable when the treatment is absent. If the parallel assumption is violated, then the estimated treatment effect may not merely capture the casual impacts of the treatment on the outcome variable. In this chapter, the trend of probability of having a new baby for Han and Non-Han women should be identical in the absence of the OCP. Otherwise the estimated ρ in regression 5.1 may not only capture the OCP treatment effects. However, given the fact that only one type of outcome can be observed (pre-treatment or post-treatment), the parallel assumption is not easy to be testified directly.

Alternatively, a more practical method is to check the existence of pre-trend right before the implementation of the treatment, by including a set of leaded and lagged treatment indicators to the regression 5.1, or as shown as regression 5A.1

$$Y_{it} = \lambda_t + \alpha_i + \sum_{j=-m}^q \rho_j D_{i,t+j} + \mathbf{X}'_{it}\boldsymbol{\beta} + u_{it} \quad (5A.1)$$

Instead of a single treatment effect as in model 5.1, I also add m ‘leads’ and q ‘lags’ of the treatment effect in regression 5A.1. ρ_j are corresponding coefficients on j th lead or lag terms. If there is no pre-trend or anticipatory effects prior to the treatment, then all the coefficients on leads should be jointly insignificantly different from zero. In practice, I include 2, 5, and 10 leads and lags into regression 5A.1 and conduct the joint test for all the coefficients on leaded and lagged terms. The F-statistic and corresponding p-value are provided in table 5A-1. The results from all three scenarios show that the coefficients on leads are jointly zero, suggesting that there is no anticipatory effects or pre-trend of the OCP in the model. Instead, regarding the joint test for the lagged terms and treatment term ($t=0$), all

results indicate that there is a significant fertility change after the OCP implementation.

Table 5A-1. Tests on Pre-trend for Various Leads and Lags

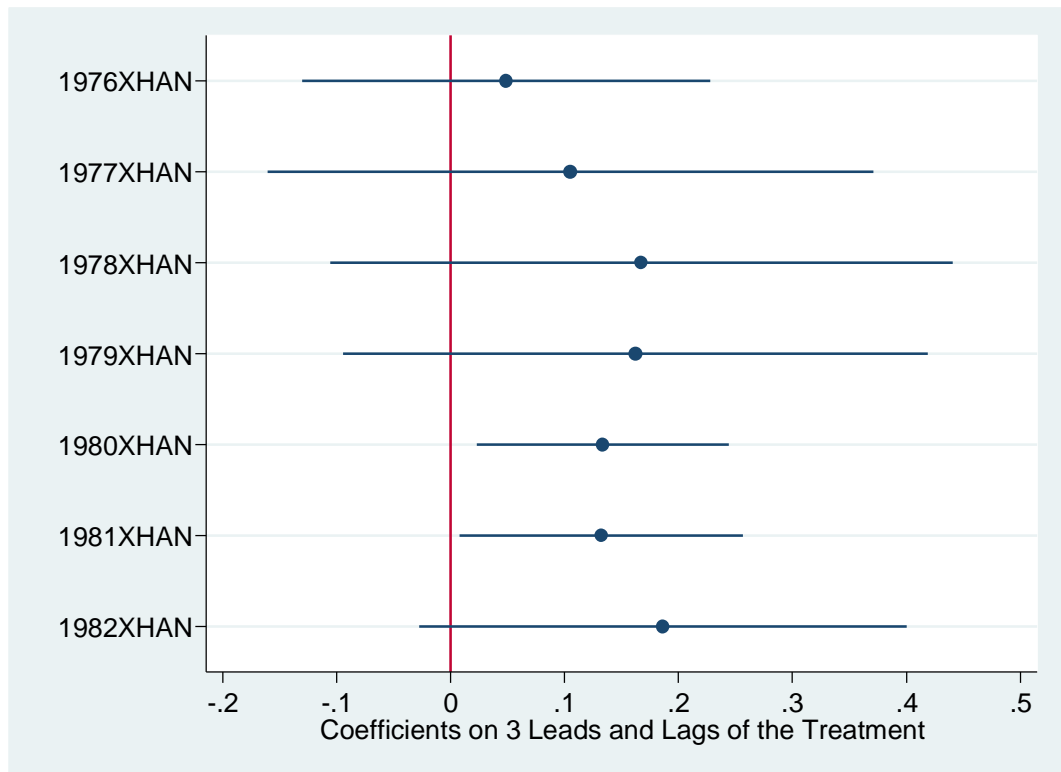
Number of Leads and Lags	2	5	10
F-Test (p-value) on Leads	0.47 (0.63)	1.71 (0.13)	1.43 (0.16)
F-Test (p-value) on Lags	20.27*** (0)	14.04*** (0)	8.70*** (0)

Note: P values of F-Test are reported in brackets. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level. The null hypothesis of the F-test is that all the related coefficients (of leads or lags) are jointly zero. The F-Test on Lags also include the coefficient on the year of treatment.

5A.2 Second Stage Robustness Check: A Test on Pre-Trend

Similar to the discussion of the OCP treatment effect on fertility reduction, it is important to verify the parallel assumption when using DD framework. I follow the same procedures that have been employed in the first stage pre-trend tests and visually present the corresponding coefficients on the leads and lags in the following figure 5A.1 with its 95% confidence intervals. Following the same practice in Autor (2003), if the coefficients on leads are close to zero, then it suggests that there is no evidence for anticipatory effects, and the common trend assumption is valid.

Figure 5A-1. Time Passage Relative to Year of the OCP Implementation



Note: The dots depict the coefficients of the leads and lags and the treatment effects of the OCP on outcome variables with 95% confidence intervals.

At the first glance, it can be concluded from the figure 5A-1 that the coefficients on the leads are not significantly different from zero, indicating that there is no anticipatory effect before the OCP implementation. It confirms that there is no pre-trend issue in the second stage estimation. However, it happens to the coefficients on the lag interaction terms as well. Particularly, the figure 5A-1 shows the evidence of a slight policy inertia as the OCP treatment effects are not significantly different from zero until 1980, one year after the OCP was implemented.²²

²² Similar empirical results are found when the leads and lags are extended to 5.

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Chapter 6. Conclusion

The widespread increase of income inequality has raised concerns regarding its potential impact on societies and economies. From the economic perspective, researchers are interested in the effect of income inequality on economic growth. Particularly, for scholars who investigate the inequality-growth nexus, China is a seemingly promising laboratory because it experienced both high speed economic growth and dramatic increase in income inequality after the economic reform. Although it is believed that moderate level of income inequality would encourage economic growth, there is still no clear definition regarding ‘moderate’. Therefore, from the perspective of policy makers, it is important to figure out if income inequality is harmful to economic growth in China. In addition, it is equally important to know what is the underlying mechanism to avoid wrong remedies. Therefore, this thesis provides new empirical evidence on inequality-growth nexus in the Chinese context by answering two research questions in three empirical chapters: is income inequality harmful to economic growth in China? And which transmission mechanism is predominant in explaining the impact of income inequality on economic growth?

The first empirical chapter (Chapter 3) examined the long-run impact of income inequality on economic growth focusing on data at the provincial level in China. It used an improved measure on income inequality which not only mitigated measurement error, but also allowed estimation via panel time series techniques to deal with non-stationarity, cross-sectional dependence, and heterogeneous coefficients. With mean group estimators on cross-sectionally augmented (autoregressive) distributed lag models, estimation results suggested that there was no significant correlation between income inequality and economic growth in China when the tests were conducted for the whole sample as the estimation results were consistently insignificant. However, when the whole sample was categorized by the economic performance, the results became different. The long-run coefficients on Theil index for the richest 10 provinces were positive while those were negative for the medium and the poorest provinces. This finding is similar to what have been concluded in Barro (2000), the study which points out a non-linear relationship that

the inequality-growth nexus is positive for rich countries while the impact of inequality on growth is negative for poor countries. But the estimation results regarding the long-run effect coefficients of the income inequality were not persistently significant across different lag lengths for each subsample.

The second empirical chapter (Chapter 4) demonstrated that empirical studies of the effects of inequality on growth that rely solely on macro data might provide misleading results. I provided a simple mathematical example that illustrated the effects of aggregating data from the level of the household in this case. Then I explored the impact of income inequality on economic growth in rural China using both village-level and household-level data. Although the results obtained from village-level data found that inequality reduced growth, consistent with the macroeconomic literature, the results derived from household data told another story: income inequality was positively associated to income growth for household with low initial income level. But such association became weaker with the increase of household income. Specifically, the households whose initial income per capita was greater than around 10,000 yuan will suffer from the adverse effects of income inequality, while the ones who live below this threshold would have a better income growth, keeping other factors unchanged. This result suggested that income inequality in rural China was an income growth driver for majority of the rural dwellers since the threshold (10,000 yuan) was much higher than the mean of the household income per capita. Such seemingly contradictory results agreed with the predictions of my mathematical example and suggested that the political economy could explain the inequality-growth nexus in rural China.

The last empirical chapter (Chapter 5) evaluated the casual effects of the One Child Policy on fertility reduction and education participation improvement within a difference-in-differences framework. The estimation results suggested that the probability of having a new child for Han Chinese women was lower than their ethnical minorities by about 2.8 percentage points, after the OCP implementation. Such effect was robust to a series of sensitivity checks. Compared to the sample mean of 7.1 percent, the treatment effect was large on fertility, taking account for almost 40% reduction of the sample mean. However, the influence of the OCP on fertility was much weaker for the educated women and urban residents. In addition,

the casual effects of the One Child Policy increased the probability of education participation of Han children aged 14-22 by about 6.1 percentage points. Compared to its sample mean of 44%, such effect took account for about 14% to the mean. It is worth to note that the policy effects on education participation was stronger for boys, suggesting the gender inequality on the chance of receiving education. Again, the One Child Policy had exerted positive impacts on increasing the probability of schooling was much stronger for rural residents. Also, from the OCP treatment effects were specifically stronger for the children between 17-20, who were more likely receiving tertiary education. Based on these estimation results, the fertility elasticity of education is -0.35, suggesting that 1% change in the probability reduction of having a child would lead to a 0.35% change in probability increment of a child (aged 14-22) to attend school. This chapter found that the One Child Policy had successfully intervened in overpopulation and human capital dilution. These findings confirmed that the endogenous fertility channel was one of the transmission mechanisms that could explain the negative impact of income inequality on economic growth in China.

Overall, with the macroeconomic data at the province level, it can be concluded that the long-run effect of income inequality is negative on economic growth, especially for poor provinces with low GDP per capita. The negative inequality-growth nexus also stands robust after dealing with the deficiencies with aggregated data.

Furthermore, combining the estimation results from both micro and macro data, this thesis suggests that the political economy and the endogenous fertility channel are predominant. Since the One Child Policy has successfully lowered the fertility and improved the human capital for the next generation, policy makers should pay more attention to the political economy channel. The findings in the thesis indicate that the high level of income inequality encourages the needs for redistribution (such as tax). However, it is such redistribution process that causes disturbing effects on the subsequent economic growth.

With these empirical evidence, there are several policy implications. First, since the income inequality is negatively associated to the economic growth in China, the policy design on reduction inequality and maintaining high economic growth can be reached at the same time. There is no efficiency-equality trade-off in the China's

context. Second, among all the inequality-reduction related policies, the most inappropriate one is using tax as the tool. Based on the empirical findings in the Chapter 4 and 5, the negative effect of income inequality on economic growth is mainly through the political economy channel. It means that the main reason for slowing down the economic growth is the disturbing effects caused by the redistribution from the governments. Third, inequality-reduction policies should be designed at the regional level, but not a national level as income inequality has different impact on provinces with different level of economic development. Last but not the least, despite the controversies of the One Child Policy, it indeed successfully reduced the fertility rate and improved the education participation. However, the policy makers should reconsider the consequences of abolishment of the One Child Policy in 2016, which could be another potential research questions in the future.

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